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Modelling the Effects of Information Campaigns Using Agent-Based Simulation

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ABSTRACT

Recent military operations in Afghanistan and Iraq have demonstrated the importance of understanding the social processes and power dynamics of local populations. The goal of this study was to simulate the process of social influence within a population using dynamic social impact theory. The simulations reproduced the characteristics of social influence such as opinion-clustering, opinion polarization, minority opinion decay, and the non-linearity of public opinion change. The study demonstrated the potential benefits and limitations of using multi-agent social simulation through a case study of a large scale public health information campaign. The study highlighted the requirement for accurate data concerning a population's social heirarchy, social networks, behaviour patterns, human geography and their subsequent impact on the success of both word-of-mouth and mass media driven information campaigns.

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Executive Summary

There is an acute lack of modelling and simulation tools available for information operations planners that assist the planning, testing, and assessment of the effects of different shaping and influencing and information operations campaign strategies. Because the information age has changed the way the military organise, train, and fight, analytical tools for simulating, quantifying, and measuring the effects of information operations have become increasingly relevant.

This paper describes the implementation of *dynamic social impact theory* within a simulation model of the process of opinion change on the issue of polio vaccination in Uttar Pradesh, India. Dynamic social impact theory asserts that where a group of people is exerting impact on an individual or another group the strength of this impact can be specified as a function of peoples' social influence, immediacy and number. Although traditional patterns of social interaction are primarily based on physical proximity, individual social status, and word-of-mouth communication, the analysis presented in this paper combines word-of-mouth communication and mass media broadcasting into a single line of analysis. The effects of individual religious affiliation and tolerance, individual volatility, population density and media restrictions on public opinion are also simulated and included in the analysis.

As is usually the case with non-linear models of public opinion formation and change, small changes in the simulation's initial conditions or characteristics of social interactions witnessed rapid changes in public opinion. The simulations invariably resulted in the emergence of spatial clusters of agents who shared the same minority opinion. Although it was not possible to validate the results of these simulations, the model nevertheless exhibited the same emergent social behaviours of opinion clustering, minority opinion decay and opinion polarization found in numerous empirically validated studies.

Recent Australian Defence Force operations in the Solomon Islands, Afghanistan and Iraq have demonstrated the importance of understanding the social processes and power dynamics of the local populations. Meeting the challenge of properly considering and assessing the impact of information operations on adversary behaviour or target population opinion over time can be aided by using modelling and simulation software to plan, test, compare, and demonstrate a large number of possible influencing strategies. The lessons learnt from designing, executing, and analysing the simulations presented in this paper will contribute to an ongoing exploration of the usability, validity, and reliability of future models and simulations for information operations.

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1. Introduction

Information Operations (IO) is a non-lethal military capability encompassing a broad range of activities and disciplines including psychological warfare, propaganda, military deception, electronic warfare, operations security, counter-intelligence, counter- propaganda, and public affairs. The combined and synchronised effects of the various components of IO working in concert with traditional munitions-based operations help to shape the modern battlefield in support of national and theatre military objectives.

Information Operations is a significant combat multiplier. It has played a role in military campaigns as far back as those fought by Alexander the Great, Attila the Hun, and Genghis Khan. Individuals such as Lord Haw-Haw and Tokyo Rose are well known for their attempts to influence allied civilians and military personnel through radio broadcasts during World War II. Vietnam was the first television war, and brought the realities of war in full colour to living rooms across the United States, a fact not lost on the North Vietnamese government and its supporters. More recent conflicts in the Balkans, Somalia, Afghanistan and Iraq have also witnessed the use of the Internet by all protagonists to conduct IO to a worldwide audience. Australian Defence Force (ADF) and Australian Federal Police (AFP) deployments in East Timor and the Solomon Islands have been accompanied by IO efforts for the purposes of force protection, correcting disinformation, defending the reputation of the ADF and AFP, and to create an environment of positive public perception of Australian Government motives [3]. To achieve such purposes requires a sound understanding of the social, religious, cultural, political, historical, and economic characteristics of different communities.

The behaviour and effects of kinetic weapons can be readily simulated on computers using a vast range of mathematical models and well-known laws from the fields of physics, ballistics, chemistry, aerodynamics, and hydrodynamics. More structured forms of combat such as trench warfare can also be represented quantitatively using differential equations such as those proposed by Lanchester in 1914 [16]. Elaborate computer models of numerous interacting weapon systems allow military strategists and analysts to test new doctrines in undersea, surface, air, land, and cyber warfare.

Social processes are harder to assess and model since the outcomes are psychological and sociological rather than physical. This can present problems when attempting to predict the success of IO compared with kinetic or force-on-force encounters. Actions taken to effect a desired change in adversary behaviour or influence the decision making processes of an adversary can take long periods of time to become effective. As a result, accurately quantifying the effects of an IO campaign on adversary behaviour or target population perceptions over time is a significant challenge, especially when faced with the uncertainty of military operations and an adaptive adversary [7]. In addition, direct testing and experimenting with current, new, or novel IO concepts is more difficult than with kinetic operations whose effects are generally instantaneous and observable.

Computer simulations can provide considerable insight into the complex nature of modern warfare and can model a military unit's behaviours and operational characteristics with a high level of fidelity. Modelling and simulation hold many advantages for the military. Modelling and simulation increase understanding, increase confidence, and decrease risk for decision-makers and military personnel. They support operational rehearsals, training exercises, and military education using realistic data on enemy dispositions and capabilities.

The success and widespread acceptance of modelling and simulation in the kinetic aspects of warfare leads to the question, "Can IO benefit from modelling and simulation?" A strong modelling and simulation capability in IO could provide decision support for choices among alternative courses of action, provide insights into the effectiveness of the chosen alternative, aid IO planning staff in evaluating various courses of action and objectives, and help in estimating the target's actions under different scenarios. Modelling and simulating IO could help to increase the quality of IO through simulation-based training that faithfully represents the dynamic nature of IO. A rigorous and mathematical approach to IO simulation could also help to strengthen the links between the 'soft science' of IO and the 'hard science' of quantitative military operations research [7].

The 1990s have witnessed the beginning of the information age and as a consequence, information will also have a far-reaching effect on warfare. It has changed the way the military organize, train and fight [35]. Analytical tools for quantifying and measuring the effect of IO have become increasingly relevant. Information Operations staff need tools to test, monitor, and evaluate IO at the sophistication level equal to or greater than their civilian counterparts in marketing and political campaigning [13]. Modelling and simulation of IO campaigns can also assist in the development of relevant measures of effectiveness (MOEs).

Unfortunately, modelling and simulation in the field of shaping and influencing lags behind conventional force on force or kinetic modelling [7]. There is a lack of models and simulations that could represent and predict influences of non-lethal IO actions and this adds to the challenge of properly considering and assessing the impact of IO actions in the Effects Based Operations (EBO) planning process [35].

Information operations is a core military competency of an EBO capability and hence tools that can help IO planners understand the social, religious, cultural, political, historical, and economic characteristics of different communities are extremely important [13]. The better IO planners understand the local population's social and religious dynamics, the less likely they are to make errors that alienate the population and the more likely the mission is to succeed. Although software simulations that can aid the IO planner have been very slow to materialize, there are some groups that have made progress in developing agent-based models that simulate the social networks, social grievances, and social systems of several Middle Eastern countries[1]. Computer simulations that use agent-based modelling represent one of the most effective methodologies for modelling complex sociological phenomena [19].
The purpose of this study is to simulate the social influence mechanisms within a target society. The results of the simulations will enable an analysis of how public opinion spreads and how various factors such as physical proximity, religious tolerance and media influence interact to sway, or support, the population's opinion. The emphasis is on identifying patterns

[1] The Complex Systems Group at Los Alamos have been working on the Threat Anticipation Program (TAP) under the direction of Ed MacKerrow which uses agent based simulation to create a short virtual history of the Middle East [19].

and trends that can inform IO strategy development rather than formal hypothesis testing of different IO strategies.

The following chapter outlines the history of agent-based social simulation and identifies and describes in detail an empirically verified model of social influence named *dynamic social impact theory* [17] that is suitable for use in an agent-based simulation.

Chapter three provides a description of the case study, the polio eradication campaign in India, which serves as the background for the simulation. The 'landscape' the agents inhabit, along with the agents' attributes and rules of behaviour, are also described in detail. Some of the assumptions and limitations of this type of simulation are also outlined.

The results of the simulations are presented in Chapter four. Much of the analysis relies on visual observation of the direction and magnitude of opinion changes and opinion clustering. The effects of altering various simulation parameters such as media influence, religious affiliation, population density, and variability in individual decision-making behaviour are also presented and discussed.

Chapter five discusses the assumptions and limitations of the study, as well as the problems of validation and data availability in large scale social simulations.

The final chapter outlines some ideas for future research and summarises the findings and some of the lessons learned from the study.

2. Simulating Social Influence

The objective of this chapter is to discuss the origins and key themes in the fields of social influence modelling and multi-agent social simulation. A detailed explanation of how social influence is modelled in the simulation is also included.

2.1 Social Influence

Social influence is a branch of social psychology[2] that looks at the characteristics of successful and unsuccessful persuasion, as well as compliance, obedience, and resistance to authority. Individuals and groups can be influenced by verbal and non-verbal means. It is important to distinguish between the terms persuasion and compliance. Compliance does not involve a change of attitude. For example, the use of heavy penalties to ensure compliance to drink-driving laws may still leave drivers with the idea that there is no harm in drink-driving and that they would drink drive if it weren't for the penalties. Successful persuasion seeks to bring about a change in an individual's beliefs or attitudes about the behaviour. Significant changes in belief or shifts in attitude regarding a certain issue or phenomenon are generally expected to drive a change in behaviour related to that issue.

Social influence has its own terminology to describe the various components of the influence process. In 1948 Lasswell [29] developed a transmission model of communication consisting of five components:

- Source – the person who is trying to influence or persuade another person
- Message – what the source is trying to convince the target of
- Target – the person who the source is trying to influence
- Channel – the method used to deliver the message
- Impact – the target's reaction to the message.

Although Lasswell was primarily interested in mass communication, his transmission model can still be applied to face-to-face or person-to-person communication. Other models of human communication, such as the Shannon-Weaver and Osgood-Schramm Circular models incorporate feedback loops into the communication process, arguing that communication is a circular, rather than linear, process [29].

The arguments a source individual or group makes and the tactics and methods they use to persuade their targets are called their *advocacy*. If an individual's advocacy is successful, then they are considered to have changed another's belief. One of the most influential researchers in the field of social influence was Carl Hovland [29]. Hovland conducted empirical research into the effectiveness of educational campaigns, publicity campaigns, advertising, propaganda, and their effects on behaviour and opinion as well as isolating the various

[2] Social psychology attempts to understand how the thoughts, feelings, and behaviours of individuals are influenced by the actual, imagined, or implied presence of others [1]

components of the communication process. His emphasis on carefully controlled experiments led communications researchers to use the scientific methods in their studies. Two of Hovland's most important contributions to the field of persuasion were in the areas of fear appeals and source credibility [29]. There are a large number of influence tactics in existence but Marwell and Schmitt's (1967) basic taxonomy consisting of sixteen influence tactics is considered the starting point for current researchers [29].

2.2 Previous Research in Social Influence Simulation

Modelling the objective factors that are in play when people try to influence one another has required a multidisciplinary approach. Contributors to the field are drawn from disciplines as diverse as statistical mechanics[3], computer science, marketing, political science, and social psychology. The simulation model of public opinion formation and social influence presented in this paper draws heavily upon Latané's *theory of dynamic social impact* [17], and further developments by Nowak, Szamrej, & Latané [23], Lewenstein, Nowak, and Latané [18], Nowak and Lewenstein [22], Kacperski and Holyst [14], and Sobkowicz [27].

2.3 Modelling Key Factors

In trying to explain the conditions where any given message will have social influence, Latané [17] emphasised the importance of the three attributes of the source - target relationship:

- Strength – the social strength, credibility, or status of the individuals involved[4]
- Immediacy – the physical or psychological distance between individuals
- Number present – the number of sources a target is exposed to.

When an individual is a target of one or more people's influence, dynamic social impact theory asserts that the level of social influence experienced by that individual can be represented by the following equation [27] :

$$I_i = -S_i\beta - \sum_{j=1,\, j\neq i}^{N} \frac{S_j O_j O_i}{d_{i,j}^{\alpha}} \tag{1}$$

where

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[3] The model has its genesis in the work of Ernst Ising, a physicist who in 1924 developed a model that imitates the behaviour of individual elements (atoms, animals, proteins, people, etc.) that modify their state in order to conform to the states or behaviour of the elements in their immediate vicinity. These are referred to as Ising models[5].

[4] This model of social influence does not attempt to differentiate between the message's plausibility and the source's credibility.

I_i represents the amount of social pressure exerted upon individual i, ($-\infty < I_i < \infty$).
O_i represents individual i's opinion (± 1) towards a proposition, where +1 and -1 represent support or opposition for a proposition, respectively.
S_i represents individual i's strength or influence ($S > 0$).
β represents an individual's resistance to change ($\beta > 0$).
d_{ij} represents the distance between individuals i and j ($d_{ij} \geq 1$).
α represents the distance decay exponent ($\alpha \geq 2$).
N is the total number of agents.

The value of β, the tendency to preserve one's own opinion or resist change was set at the value 2 to conform with the value used in Latané's research [17]. Larger values of β mean that individuals within the simulation will require greater amounts of social pressure to change their opinion than if β was set at a lower level. The value of α is set at the value 2 in all the simulations that are conducted in this study, again to conform with the variable values used in Latané's research [17]. Higher levels of α will result in a far greater acceleration of the effect of increasing distance between source and target has on the amount of social pressure exerted on the target.

Latané [17] called the distance d_{ij} 'immediacy' and noted that it is an attribute of a *pair* of individuals, and considered it a measure of the ease of communication between two individuals. The effect of physical proximity follows the law of distance decay, usually modelled as $\frac{1}{distance^2}$, that is the ease of communication decreases by $\frac{1}{distance^2}$ as source and target get further apart. The rapid decline of the ease of communication between source and target as distance between them increases is shown in Figure 1. Note that distances in this study are discrete values, not continuous.

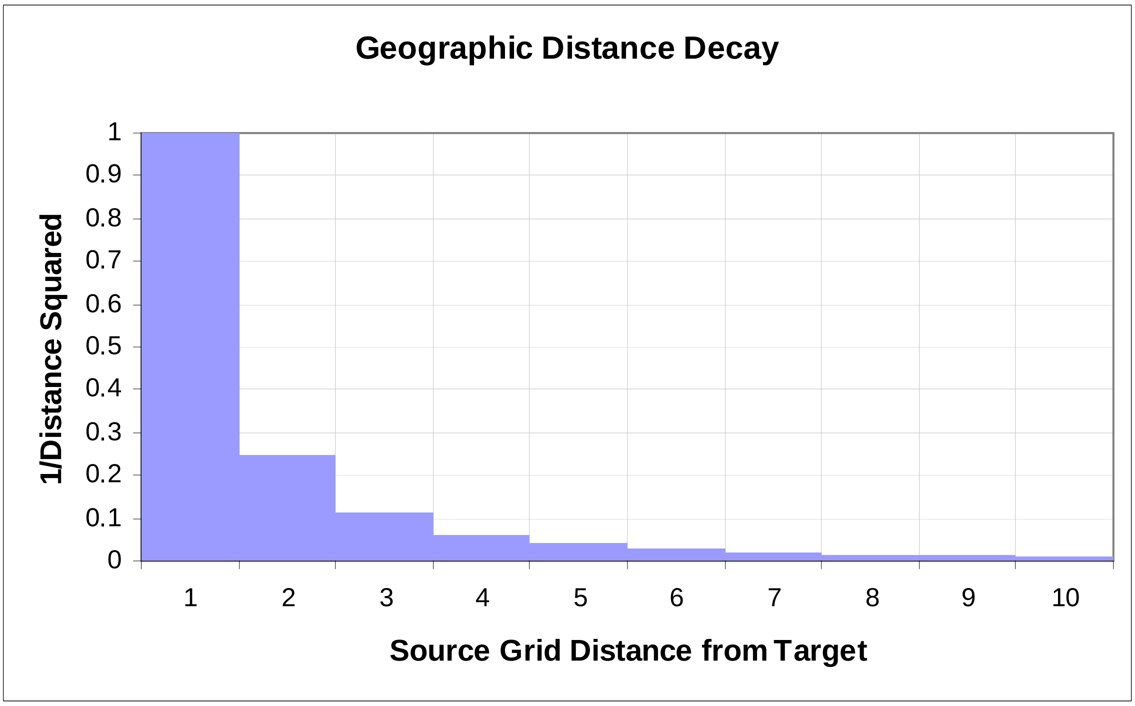


Figure 1. Ease of communication between source and target decays as the physical distance between source and target increases.

If the social pressure (I_i) on individual i is > 0, then the individual will change their opinion. The value of I_i is a deterministic force or pressure felt by individual i to change their opinion when the value of I_i is > 0. To incorporate a degree of randomness in the decision-making behaviour of individuals, Kacperski and Holyst [14] used the following rule:

$$O_i(t+1) = \begin{cases} O_i(t) \text{ with probability } \dfrac{\exp(-I_i/T)}{\exp(-I_i/T)+\exp(I_i/T)} \\ -O_i(t) \text{ with probability } \dfrac{\exp(I_i/T)}{\exp(-I_i/T)+\exp(I_i/T)} \end{cases} \tag{2}$$

where

$O_i(t)$ is the opinion (±1) of individual i at time t.

Using Equation (2) results in a sigmoid curve reflecting the probability that an individual will change his or her opinion O in the next time step t + 1 given a certain value of I_i at t. The parameter T is interpreted by Kacperski and Holyst [14] to represent the average volatility of the individuals in the simulation. The effect of various values of T on probability of opinion change given social impact score is shown in Figure 2.

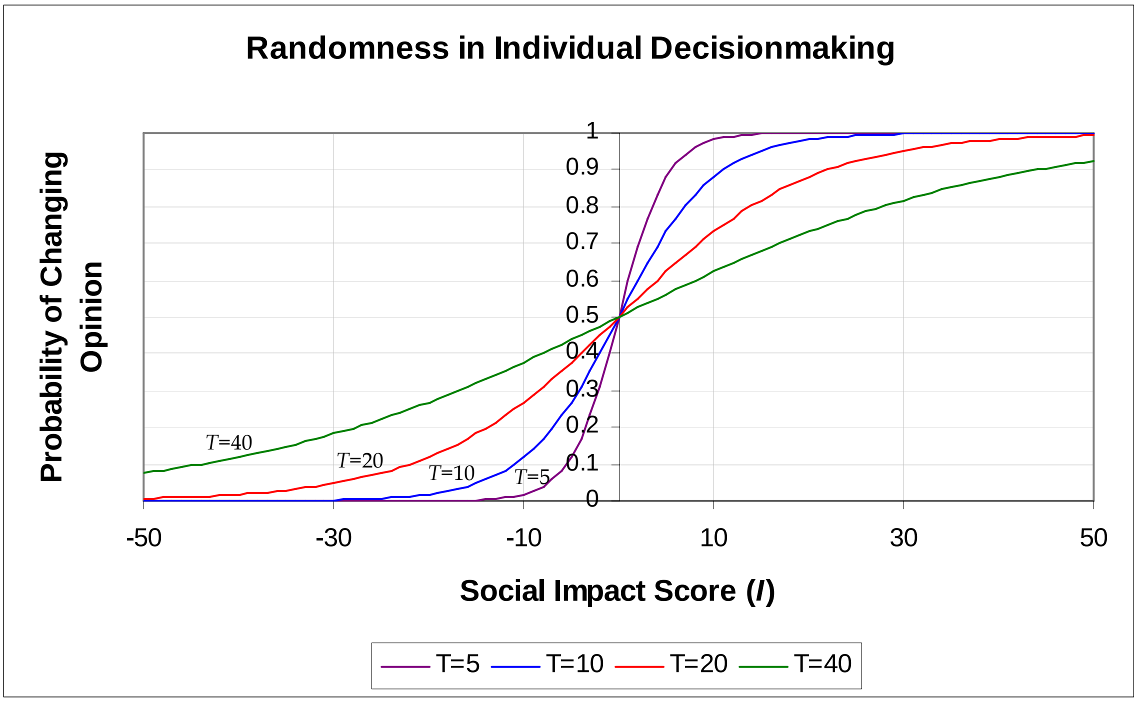


Figure 2. Effect of various values of volatility (T) on the probability that an individual will change opinion given a certain level of social pressure (I) exerted upon him.

For example, if an individual is subjected to a social pressure score of $I = 10$ by his neighbours, and the value of $T = 5$, the probability that he will change his opinion on a certain issue is 0.98. If the value of $T = 40$, the probability that he will change his opinion under the same social pressure from his neighbours ($I = 10$) is only 0.62. Lower values of T mean that the opinions of individuals in the simulation are highly dependent on their neighbour's opinions (I), whereas higher levels of T reduce the power of I in determining an individual's opinion. This also applies to situations where the social pressure (I) is < 0 and the pressure is on the individual to maintain their current opinion. At lower levels of T the opinion is highly likely to be maintained, whereas at higher levels of T, the likelihood of maintaining an opinion in accordance with social pressure from neighbours is much lower. Higher levels of T, or volatility in individual decision-making, make it more difficult to predict whether an individual will support or oppose an issue.

External global influences (such as mass media) can also be included in the model by adding the following term to Equation (1):

$$-O_i O_M S_{M_i}$$

where

S_{Mi} represents the strength or influence media messages have on individual i
$S_{Mi} > 0$
O_M is the opinion of the media (±1)
O_i is the opinion of individual i (±1).

The incorporation of media effects into Equation (1) results in a social impact model of the form:

$$I_i = - S_i \beta - O_i O_M S_{M_i} - \sum_{j=1, j \neq i}^{N} \frac{S_j O_j O_i}{d_{i,j}^2} \qquad (3)$$

The media is modelled as another agent within the environment, but with a distance or immediacy of 1 from each individual, due to its omnipresent nature. The value of S_{Mi} will vary from one individual to the next, thus each individual will feel a different level of pressure exerted on him by the media. The value of S_{Mi} is analogous to the amount of credibility or trust an individual places in information he receives from the media.

The model is quite straight forward when the distance is a single ratio measure such as geographical distance or time, but complications can arise when other measures of distance such as religion, race, gender, or income are used, or a combination of distance measures is desirable. These complications will be explored in further detail in Section 2.7.

Latané [17] validated his simulations with empirical data gathered from studies of patterns of communication in various parts of the world such as China, Poland, and the US. Having real-world validation of the equations and processes outlined above is one of the advantages of working with this particular model. We therefore consider the basic equations driving the simulations to be largely validated.

2.4 Cellular Automata

The field of cellular automata (CA) has its origins in the work of John von Neumann and Stanislaw Ulam in the late 1940's [37]. Von Neumann's work on computer programming and design led him to seek a theory that would include the important similarities between computers and natural organisms as well as the common principles concerning the structure and organisation of both natural and artificial systems. Von Neumann called his general theory of computers the "theory of automata" which was later changed to the "theory of self-reproducing automata" [37].

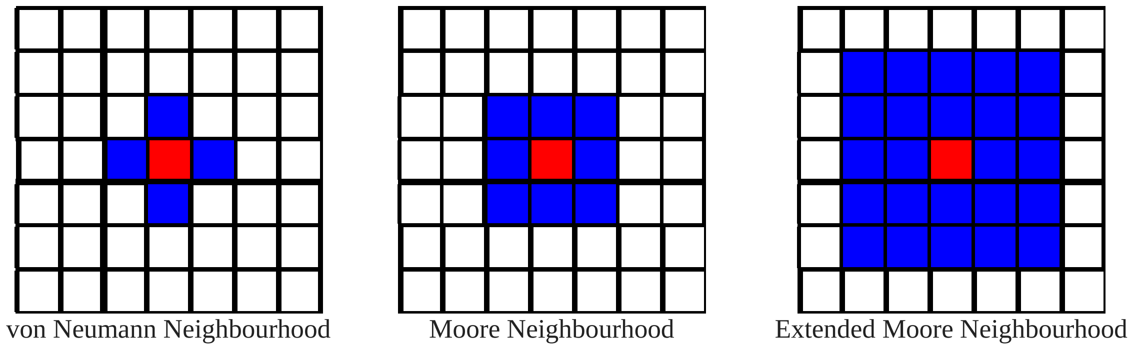
A wide variety of CA models and transition rules have been developed since the 1950's and adapted for a variety of modelling purposes in many areas including physics, computing, biology, and meteorology [37, 38, 39]. Despite the large number of CA models in use in different fields, all CA models share the same basic features:

- Cells are arranged in a regular D-dimensional grid
- Every cell adopts a state from a finite set of states
- Time is discrete
- Cells change their states according to local rules
- The same transition rule applies to all cells

- In each period cells are updated (simultaneously or sequentially).

Cellular automata models are usually implemented using a two-dimensional grid of square cells or automatons. A cell's different states are usually represented on the computer screen by different colours. The execution of the model is displayed on a computer screen as a sequence of changing patterns and colours as the cells interact with each other over time. At each increment of the simulation's time counter the values in all the cells are simultaneously updated according to a set of state transition rules. These rules take into account a cell's state as well as the states of the cell's neighbouring cells before updating the cell with its new value.

There are different types of neighbourhoods in CA models. In a two-dimensional grid the following three neighbourhoods are the most common:



The blue cells make up the red cell's neighbourhood. The states of the blue cells are used to calculate, according to pre-defined rules, the red cell's state in the next time step. The simulations documented in this paper all use an extended Moore neighbourhood.

The advantage of CA models is that they can describe the behaviour of complex systems using the interaction of cells on a grid following simple rules. The simplicity of the CA approach is in stark contrast to the more traditional approach that uses partial differential equations to describe the behaviour of complex systems.

2.5 Social Influence Simulation Using Cellular Automata

One of the first applications of cellular automata to social science was the work of Schelling [26] who devised a simple model of racially diverse neighbourhoods in which individuals preferred at least a certain fraction (25%) of their neighbours to be the same colour as them. He found that even relatively tolerant populations composed of individuals who were comfortable having 75% of their neighbours be of a different colour than their own invariably, and unexpectedly, produced markedly segregated neighbourhoods or ghettos. Probably the most well known example of two-dimensional cellular automata among non-specialists is Conway's *Game of Life* [6]. Further research by Wolfram [37, 37, 38] took a more systematic approach to the investigation of the behaviour of cellular automata and did much to revive interest in a field that was largely viewed as more of a recreational pastime of some computer scientists than an academic topic.

Two of the main advantages of using an agent-based approach to modelling dynamic social systems are its ability to incorporate heterogeneity into the simulation and its ability to produce emergent behaviour [2, 11]. Firstly, using agents allows heterogeneity to be taken into account in the community under study. The entities (e.g. individuals) in the community are able to have differing opinions, information, beliefs, incomes, religions, and loyalties. This level of heterogeneity is difficult to model mathematically. Simulations that use predominantly differential equations tend to assume homogeneity in order to make the model mathematically tractable. Incorporating heterogeneity into the model allows for a more realistic representation of the system being studied. Secondly, agent-based simulations allow easier and more realistic modelling of fluid or turbulent social systems. Collective and emergent phenomena that are characteristic of complex dynamic systems, such as flocking and tipping points, are easily reproducible using agent-based simulations.

Emergent, or bottom-up, behaviour is demonstrated when a number of entities form more complex behaviours as a collective. Emergent behaviours are not easily predicted or deduced from the behaviour of the lower-level entities. One of the most important points to consider with regard to emergence is that it challenges the assumption that complex behaviour must always be a result of complex rules [2, 12]. Flocking or swarming is considered to be an example of emergent behaviour. According to Huberman and Adamic [12], flocking is controlled by three simple rules: avoid crowding neighbours, steer towards neighbour's heading, and steer towards neighbour's location. Following these simple rules creates complex motions and interactions from which the behaviour of the flock emerges as a whole.

Using cellular automata to build a working model of the social influence processes or other 'soft' aspects of a target system that are important to IO analysts requires first building a model to solve a problem. Generating a specific set of research questions or objectives, as opposed to building a general model of the target society and then generating research questions, should precede any model building [11].

The central questions this project is intended to address include:

- How well can an information campaign be represented within a computer simulation?
- What effect do the media have on the population's opinion on a certain issue?
- What effect does increasing the frequency with which a message is broadcast in the media have on population opinion towards a certain issue?
- Does the population density of the target population affect the level and rate of opinion change on a given issue?
- How important is the shape of the distribution of religious tolerance to target population opinion change rates?

2.6 Example of Dynamic Social Impact Simulation Using CA

The following example illustrates how dynamic social impact theory is implemented within a simple CA simulation. Figure 3 shows a 5 x 5 grid containing 25 individuals (cells), each with a number representing their level of social influence or social status, *S*, (the white numbers) and an opinion on a topic of interest, e.g. whether they support childhood vaccination (blue, opinion O = +1) or oppose it (red, opinion O = -1). The target is in the centre of the grid and has strength S = 9 and supports childhood vaccination. The target is subjected to the influence of eight neighbours of distance = 1 and 16 neighbours of distance = 2, all of whom will have some influence on whether the target maintains his support for vaccination or changes his opinion.

The target's neighbours all have varying levels of individual social influence, *S*. Each individual's level of social influence is randomly drawn from a uniform distribution with range [1, 15] (inclusive). Opinions for or against childhood vaccination (blue or red, respectively) are randomly assigned to individuals using a Bernoulli distribution where the probability of an individual supporting vaccination, *p*, has the value of 0.5 and the probability of opposing vaccination, (1-*p*), has the value of 0.5.

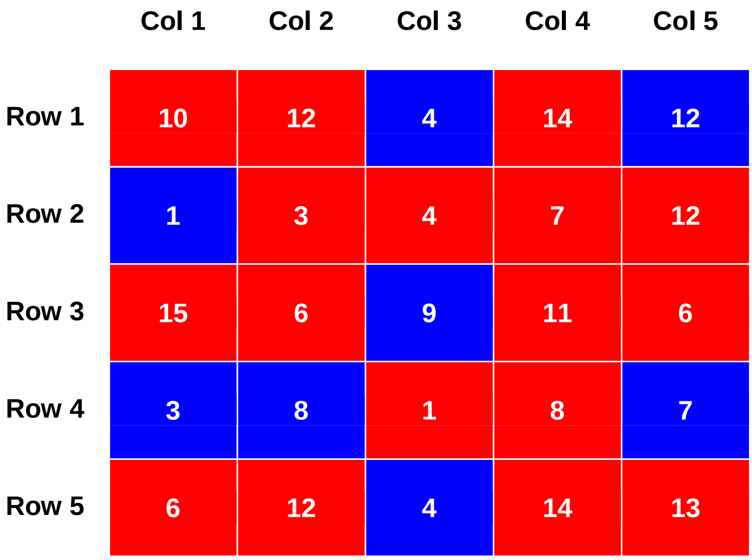


Figure 3. 5 x 5 grid of randomly distributed opinions and social influence levels. Target cell with a value S = 9 is in the centre of the grid (row 3, column 3).

Table 1 shows how the social pressure exerted on the target cell is calculated. Rows and columns are designated by *r* and *c*, respectively. Calculating the influence each neighbour exerts on the target, is simply a matter of using the equation:

$$\frac{S_j O_j O_i}{d_{i,j}^2} = \frac{\textit{neighbour's social influence} \times \textit{neighbour's opinion} \times \textit{target's opinion}}{(\textit{neighbour's distance from target})^2}$$

Table 1. Implementation of social impact equation.

Neighbour's Location (r, c)	Neighbour's Social Influence	Neighbour's Opinion on Vaccination: -1 = oppose vacc. 1 = support vacc.	Target's Opinion	Neighbour's Distance from Target	(Neighbour's Distance from Target)^2	Social Pressure Exerted on Target Cell by Neighbour
2,2	3	-1	1	1	1	-3
2,3	4	-1	1	1	1	-4
2,4	7	-1	1	1	1	-7
3,2	6	-1	1	1	1	-6
3,4	11	-1	1	1	1	-11
4,2	8	1	1	1	1	8
4,3	1	-1	1	1	1	-1
4,4	8	-1	1	1	1	-8
1,1	10	-1	1	2	4	-2.5
1,2	12	-1	1	2	4	-3
1,3	4	1	1	2	4	1
1,4	14	-1	1	2	4	-3.5
1,5	12	1	1	2	4	3
2,1	1	1	1	2	4	0.25
2,5	12	-1	1	2	4	-3
3,1	15	-1	1	2	4	-3.75
3,5	6	-1	1	2	4	-1.5
4,1	3	1	1	2	4	0.75
4,5	7	1	1	2	4	1.75
5,1	6	-1	1	2	4	-1.5
5,2	12	-1	1	2	4	-3
5,3	4	1	1	2	4	1
5,4	14	-1	1	2	4	-3.5
5,5	13	-1	1	2	4	-3.25
Sum of social pressure exerted on target cell by all 24 neighbours =						**-52.75**

The rows in the column named 'Pressure exerted on target cell' represent the social pressure each neighbour exerts on the target cell. The social pressure the target cell is subjected to by its neighbours is given by:

$$\sum_{j=1,\, j\neq i}^{N} \frac{S_j O_j O_i}{d_{(i,j)}^{\alpha}}$$

If the 'stubbornness' or resistance to change parameter is set to β = 2 and α = 2, using Equation (1) the result becomes:

$$I = -9 \times 2 - (-52.75) = 34.75$$

If the value of $T = 0$ the system is noiseless and the rule outlined in Equation (2) becomes deterministic. In this case, since $34.75 > 0$, the target will have a different opinion at time $t + 1$. A system that contains no noise is not very realistic; therefore the parameter T is set to a value of 20 to make the system appear noisier and less deterministic. The probability that the target will change its opinion in the next time step ($t + 1$) then becomes:

$$\frac{\exp(34.75/20)}{\exp(34.75/20) + \exp(-34.75/20)} = \frac{5.683118}{(5.683118 + 0.17596)} \approx 0.97$$

Within the simulation a random number x is drawn from a uniform distribution [0, 1]. If $x \leq 0.97$, then the opinion at $t + 1$ will be changed. If $x > 0.97$ the opinion of the individual at time $t + 1$ will remain unchanged. The example presented above can be calculated easily using a spreadsheet or done by hand, but employing a computer simulation package allows simulations containing many thousands of agents to be run.

2.7 Representing Social Distance

In an attempt to make the model more realistic, several issues regarding distance need to be addressed. Geographical distance (d_{GEO}), or physical proximity, is defined as the grid distance between two individuals. Although geographical distance is an important factor in determining the frequency and intensity of interpersonal communication, it has often been ignored by social scientists [15, 31]. In addition to physical propinquity, other types of distances, or factors that influence the likelihood of communication between individuals should also be included in Equation (3). Studies carried out by McPherson, Smith-Lovin, and Cook [20] indicate that people tend to have significant contact with others who share similar attributes. This tendency to form social networks with others who share similar socio-demographic characteristics is known as homophily and has a powerful effect on the information individuals receive, the attitudes they form, and the interactions they experience.

One of the major factors influencing who individuals mix and communicate with is race or ethnicity, with age, religion, education, occupation and gender following in approximately the same order [20]. Although these factors and their order of importance may vary from culture to culture, they nevertheless provide a starting point to further extend Equation (3) by incorporating other measures of distance.

Unlike physical measures such as geographic distance, measures such as ethnic or religious distance are more difficult to quantify. If religious distance, for example, was to be made part of the social influence model, then Equation (3) can be rearranged to incorporate both geographic and religious distance:

$$I_i = -S_i\beta - O_i O_M S_{M_i} - \sum_{j=1, j\neq i}^{N} \frac{S_j O_j O_i}{\left(w_1 d_{GEO(i,j)} + w_2 d_{REL(i,j)}\right)^2} \tag{4}$$

where

$w_1 + w_2 = 1$

geographical distance = d_{GEO}

religious distance = d_{REL}.

$d_{GEO} \geq 1$

$d_{REL} \geq 1$

Additional measures of distance can be incorporated using the general form:

$$I_i = -S_i\beta - O_i O_M S_{M_i} - \sum_{j=1, j\neq i}^{N} \frac{S_j O_j O_i}{\left(w_1 d_{1(i,j)} + w_2 d_{2(i,j)} + \cdots + w_P d_{P(i,j)}\right)^2} \tag{5}$$

where

$w_1 + w_2 \ldots + w_p = 1$

$0 \leq w_i \leq 1 \quad \forall i$

$d_{(i,j)} \geq 1$ ($\forall$ distances $d_1 \ldots d_p$)

Establishing a distance measure between two religions is not straightforward. Unlike geographic distance, the units of measurement between two religions are not apparent.

Social distance between groups or individuals has traditionally been measured using the Bogardus Social Distance Scale, developed in 1925 by Emory Bogardus [4]. Bogardus was an influential American sociologist best known for his development of the Social Distance Scale. Much of Bogardus' work was in the area of race relations. In an attempt to measure social distance among different groups of people, Bogardus constructed a survey questionnaire to determine a social distance quotient. The Bogardus Social Distance Scale is shown in Table 2:

Table 2. Bogardus Social Distance Scale [4].

Attitude towards ethnic group	Negro	Mexican	Asian
1. Would marry			
2. Would have as guest in household			
3. Would have as next door neighbour			
4. Would have in my neighbourhood			
5. Would have in same town			
6. Would prefer they live outside my town			
7. Would prefer they live outside my country			

The social distance variables are arranged in rows, while the group names are arrayed as column headings. The respondent is instructed to tick one of the seven rows for each ethnic group as their feelings dictate. The scale is scored so that the responses for each ethnic group are averaged across all respondents, yielding a Distance Quotient (DQ) (Bogardus called it Racial Distance Quotient), with a minimum of 1.0 and a maximum of 7.0.

Each of the seven response items has a geometric parallel in that increasing levels of disdain have an explicitly geometric distance representation. For example, *would marry* represents the closest geometric distance possible, while *live outside my country* generally represents thousands of kilometres of geometric distance. In 1954, Dodd and Nehnevasja [8] introduced geometric distances into a modified Bogardus Scale (Table 3):

Table 3. Dodd and Nehnevasja 1954 Bogardus Response Items [8].

Attitude	Geometric Equivalent
1. Would marry	10^0 metres (1 metre)
2. Would have as guest in household	10^1 metres (10 metres)
3. Would have as next door neighbour	10^2 metres (100 metres)
4. Would have in my neighbourhood	10^3 metres (1 kilometre)
5. Would have living in same town	10^4 metres (10 kilometres)
6. Would have live outside my town	10^5 metres (100 kilometres)
7. Would have live outside my country	10^6 metres (1,000 kilometres)
8. Would kill	10^7 metres (10,000 kilometres/removed from planet)

By converting each item in the Bogardus scale to a geographic distance, Dodd and Nehnevasja [8] were able to capture a rough, but common sense, physical distance for each item on the questionnaire. Their objective was to translate human emotions into objective measures of distance. They also added an additional item, "would kill", given the amount of ethnically motivated killing that is commonplace in some parts of the world.

The simulations in this study employ a similar, albeit abbreviated, method of associating statements of religious tolerance with grid distances on the simulation landscape. Using Dodd and Nehnevasja's [8] approach, religious distance, for example, can be translated into the geographical distance units required by Equation (4). This allows both geographical distance and religious distance to be incorporated into a single equation.

2.8 Implementing Social Distance Scales in CA Simulations

The following example illustrates how the concepts of social distance and social distance quotients discussed in the previous section are implemented within a CA simulation. Table 4 shows a modified Bogardus scale used as the basis for transforming an agent's qualitative statements of religious tolerance into quantitative simulation grid space equivalents between 1 and 32 (within the simulation the maximum geographical distance an agent can feel, or be influenced by, another agent's opinion is 32 grid spaces. This is explained in further detail in Section 3.3).

Agents choosing smaller grid distances, such as one to four spaces, between themselves and agents of another religion indicate a greater willingness to frequently interact with an individual of a different religion. Agents choosing larger grid distances, such as 10-32, indicate higher levels of hostility towards individuals of a different religion.

Table 4. Modified Bogardus scale for establishing religious distance.

Feelings Towards Other Religion:	Geometric Equivalent
1. Would have as spouse, friend, or neighbour	1 grid space
2. Would have living in my street or neighbourhood	2-4 grid spaces
3. Would have living in my town or city	5-9 grid spaces
4. Would prefer they live outside my town or city	10-18 grid spaces
5. Would prefer they live outside my country	19-32 grid spaces

When the simulation program creates an agent, it gives it a religion, a location, an influence level, an opinion on polio vaccination, and it also randomly assigns it a religious tolerance number between one and five based on the row number in Table 4. Hindu agents are randomly assigned a preferred distance from Muslim agents, and vice versa. Within each item of Table 4 there is an increasing range of grid spaces the source can be located from the target. A further random number is drawn from this range of grid spaces to produce a single number representing the grid distance from the target the target would *prefer* the source to be. For example, if an agent was randomly allocated feeling #4, *would prefer they live outside my town or city,* from Table 4, a further random number between 10 and 18 (inclusive) would then be drawn to represent a geometric equivalent of statement #4. An example of how this works within the simulation is shown below.

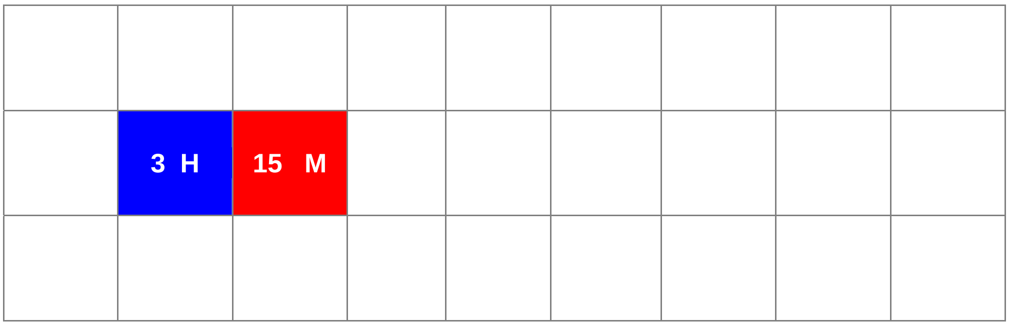


Figure 4. Agents with different religions.

In figure 4, the blue agent 3H (the influence *target*) has a pro-vaccination opinion (1), belongs to religion H, and has a social influence of 3. Living next door, the red agent (the influence *source*) has an anti-vaccination opinion (-1), belongs to religion M, and has a much higher social influence of 15. Without taking religion into account, the social pressure the source agent 15M would be able to exert on the target, agent 3H, can be calculated using Equation (1) as follows:

$$\textit{social impact of source 15M on target 3H} = (-3 \times 2) - \left[\frac{-1 \times 1 \times 15}{1^2} \right] = 9$$

Since the social impact the source 15M exerts on the target 3H is > 0, the target, agent 3H will change its opinion and oppose polio vaccination.

If religious tolerance was taken into account then agent 3H would have 'filled out' the modified Bogardus questionnaire shown in Table 4 when it was created. For this example, assume agent 3H has randomly chosen item three, *live in my town or city*, to represent his feelings towards agents with a different religion than his own, and then randomly chosen a number from the ranges within item three a final preferred grid distance value of, for example, seven for agents of a different religion to his. Because source 15M is affiliated with religion M, and target 3H is affiliated with religion H, their religious distance (the target's *preferred geographical distance* between them) of seven grid spaces attenuates 15M's influence on 3H as follows:

$$\textit{social impact of source 15M on target 3H} = (-3 \times 2) - \left[\frac{-1 \times 1 \times 15}{(0.5 \times 1 + 0.5 \times 7)^2} \right] = -5.0625$$

Since the social influence the source exerts on the target is < 0, agent 3H will not change its mind and will retain its pro-vaccination stance (*Note the weights of 0.5 applied to both geographic and religious distance in the above calculation*).

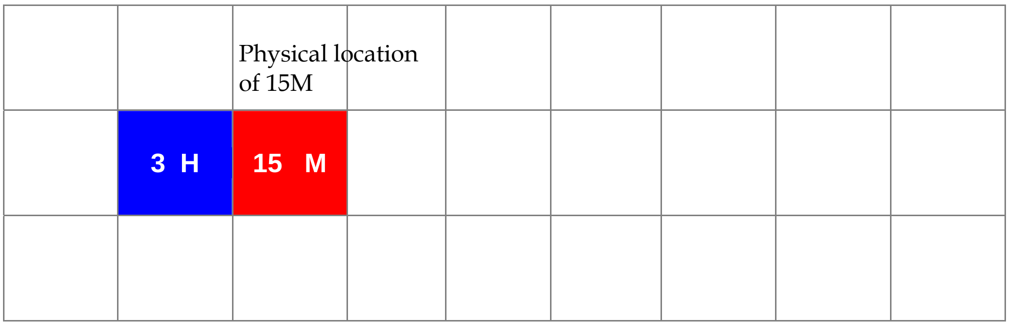


Figure 5. Physical distance between source (15M) and target (3H).

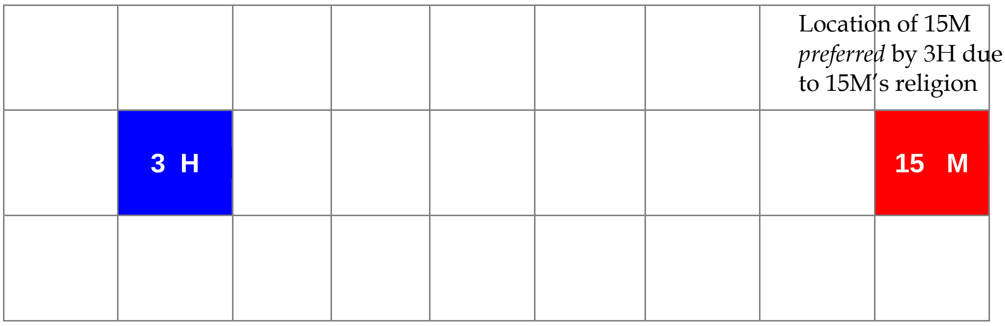


Figure 6.Distance from target (3H) would prefer source (15M) to be as a result of religious difference.

Because the final distance measure is really a weighted combination of the source's actual and preferred distance from the target, the combination of distances results in a final distance of: (0.5 * 1 + 0.5 * 7) = 4. A distance of 4 grid spaces can be thought of as a weighted location, as shown in the following diagram:

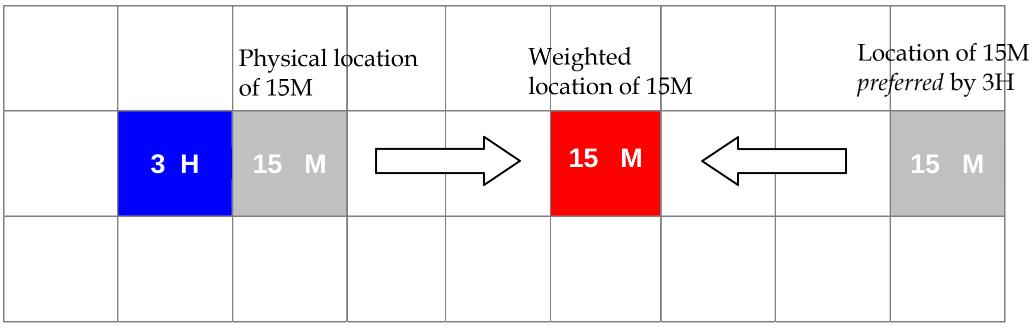


Figure 7. Weighted location of source agent 15M.

If a different weighting scheme was chosen and more weight was placed upon the source agent's geographic location than their religious affiliation, the source agent 15M would have more influence over the target agent 3H. In reality, different societies would produce different distributions of tolerance statements, so the ability to tailor religious tolerance using different weights and distributions within the simulation is useful. Simulation results with differing weights and religious tolerance distributions are presented in the analysis section.

3. Case Study: Polio Eradication Campaign in India

The objective of this chapter is to describe in detail the case study which formed the basis of the simulation, describe the 'landscape' the cells inhabit, and state the attributes and rules the individual automata must follow during the course of the simulation. Basing the simulation on a real public information campaign brings into focus the benefits and limitations of social simulation when it is applied to a real world problem. The simulations are intended to demonstrate how public opinion spreads and how various factors such as physical proximity, religious tolerance and media influence might interact to sway, or support, the population's opinion on an important issue.

3.1 The Polio Eradication Campaign in India

In 1988 the World Health Organisation (WHO) set a global polio eradication goal for 2005. When the WHO announced its polio eradication initiative in 1988, India reported 24,257 cases of polio. As a result of the polio eradication initiative, this number had fallen to 2,765 by 1997. The Indian government undertook an information campaign to educate parents on the benefits of polio vaccination for their children.

The polio vaccination campaign depended on announcements using radio, print, television, cinema, and posters to influence the public, with television and radio playing a more important role in the urban areas [28]. Apart from the pro-vaccination messages delivered through the mass media, health workers were the main source of awareness for both rural and urban parents.

Unfortunately, many groups within the target population rejected the message to have their children immunised for a variety of reasons. The most salient and controversial reason for rejecting vaccination was the rumour among some poorer and less-educated Muslim communities that the vaccinations were designed to sterilise Muslim children as part of a well-disguised form of genocide implemented by the Hindu-dominated Indian Health Department [34]. Other problems faced by the information campaign included illiteracy, difficult to reach slums and rural areas, areas controlled by militant groups, difficulty in contacting nomadic communities, a middle class avoidance of 'public' health activities, doubts over the quality of the vaccination, and a distrust of western medicine. Distorted, negative, and inaccurate reporting by some sections of the media also caused much confusion in the population [28].

Simulating aspects of the Indian government's polio information campaign in the state of Uttar Pradesh provided an unclassified test bed for demonstrating how IO campaigns can be modelled and simulated using Latané's dynamic social impact theory within a cellular automata framework [17]. Past IO campaigns conducted by the ADF in various countries share a number of similarities to the case study.

3.2 Demographics of Uttar Pradesh, India

Much open source data exists on the demographics of Uttar Pradesh, India. Building a simulation that approximates the distribution of religion, gender, age, population density, etc. is not difficult, although it is very tedious and time consuming. The density and location of the cells in the simulation's map is a very rough representation of the actual population densities within the state of Uttar Pradesh. Representing built up urban areas such as Delhi, Agra, Kanpur, Varanasi, and Gorakhpur was done by placing automata very close together in the location of those cities. Rural areas were represented by distributing automata more sparsely over the remaining areas of Uttar Pradesh. In accordance with Uttar Pradesh's demographics, approximately 70% of the population are Hindu and 30% are Moslem. Figure 8a shows a map of Uttar Pradesh and Figure 8b shows the distribution of agents superimposed on the map.

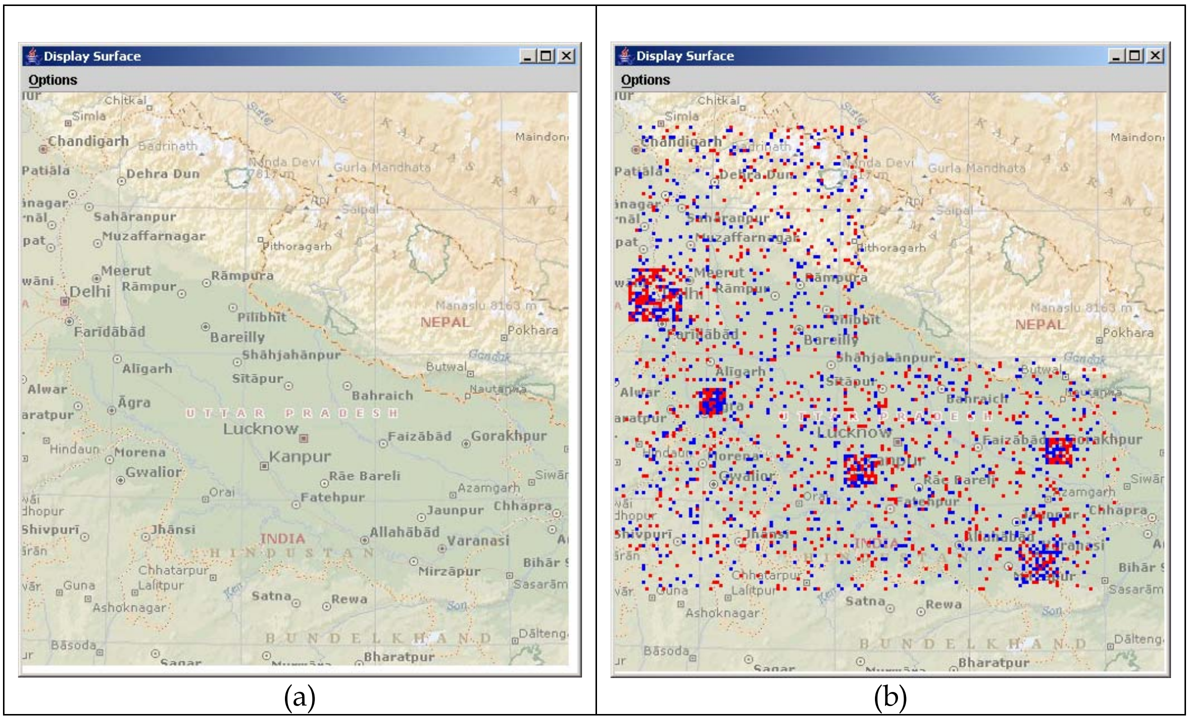


Figure 8. Map of Uttar Pradesh used in the simulation (a), and proportional distribution of households across the state (b). Households supporting polio vaccination are coloured blue, while those opposing polio vaccination are coloured red.

Each cell in the landscape can be considered as an individual household. The colours of the cells represent the household's opinion towards polio vaccination, with blue indicating support for polio vaccination, and red indicating a rejection of polio vaccination. When an individual household, or head of the household, changes their opinion on vaccination, they also change their colour. This allows a visual representation of the initial distribution of opinions, as well as a means to witness the non-linear dynamics of social influence, information diffusion, social clustering and tipping points (phase shifts). The simulation also collects various statistics over the course of the simulation that can be plotted as the simulation progresses or analysed separately using statistical analysis software such as SPSS, Excel, or Minitab.

3.3 Initialising a Cellular Automaton's Attributes

The automata in this simulation have the following attributes:

- Geographic location (x, y) coordinates
- Religion: { Hindu, Moslem }
- Social influence (or persuasiveness): Normal (mean = 5, variance = 4)
- Resistance to change constant: 2
- Susceptibility to media influence: Normal (mean = 5, variance = 4)
- Preferred distance with respect to other religions: An integer between 1 and 32 inclusive
- Opinion on polio vaccination: { +1, -1 }

Note that social influence and susceptibility to media influence are truncated at zero, so their distributions cannot be considered strictly normal. Under a normal distribution with a mean of five and a variance of four, six out of every thousand values can be expected to be below zero and need to be redrawn.

Several of the above attributes can be related to variables from equation (3) in the following way:

Social influence (or persuasiveness) = S
Stubbornness or resistance to change constant = β
Susceptibility to media influence = S_M
Opinion on polio vaccination = O

At the beginning of the simulation automata are created with varying values of these attributes. The geographic location of a household is determined by the analyst insofar as the household will be near a city or located in a rural area. Approximately 30% of the households are randomly selected for placement in a built up urban area, with the remaining 70% being located at random anywhere within the rough bounds of the map of Uttar Pradesh[5]. The map measures 150 grid spaces across and 150 grid spaces vertically. A grid size of 150 x 150 allows a reasonable level of detail to be seen in a background map of Uttar Pradesh while still allowing the simulation to execute at an acceptable speed with a population of automata ranging from 2,000 to 8,000. An automaton's neighbourhood is an extended Moore neighbourhood that extends up to 32 grid spaces on all sides (Latane called this the *range of impact* [17]). This limits a target to a maximum possible number of 4,224 neighbours or sources of social influence. If the grid size is large, as in this case, then limiting the size of an agent's neighbourhood enables the simulation to execute much faster with negligible effect on the

[5] Approximately 70% of Uttar Pradesh's population live in rural areas [34].

results[6]. Due to computing power limitations, Latane used extended Moore neighbourhoods of size 10 to enable the simulations to proceed more quickly [17].

Limiting the size of an agent's neighbourhood to a maximum of 32 grid spaces on all sides means that the summation notation in Equations (1), (3), (4), and (5) needs to be modified slightly to reflect the truncation of the agent's world. Taking Equation (1) as an example, the summation is not over all the agents in the simulation, *N*, but only those agents within the extended Moore neighbourhood of agent *i*, the set of which is denoted by *N*(*i*).

$$I_i = -S_i \beta - \sum_{\substack{j \in N(i) \\ j \neq i}} \frac{S_j O_j O_i}{d_{i,j}^{\alpha}}$$

A household's religion is decided by a random variable with two possible outcomes, Hindu and Moslem. Since Hindus make up approximately 70% of the population and Moslems 30%, the probabilities of a household being assigned to the Hindu or Moslem religion are 0.7 and 0.3, respectively. A household's religion cannot change over the course of the simulation.

A household's preferred distance with respect to the other religion is determined by randomly drawing from a uniform distribution ranging from 1 to 5 (inclusive) to mimic the row numbers shown in Table 4. Unless the agent chooses row #1 in Table 4, a further random number will be drawn to determine the exact location within the range of preferred distances relevant to the agent's stated feeling. This ensures a spread of preferred distances between 1 and 32 (inclusive) grid spaces, although the spread of values in total is not uniform in terms of grid spaces. Smaller values mean greater levels of religious tolerance, while larger values mean greater intolerance. Once assigned, an agent's religious tolerance does not change over the course of the simulation. This is explained in more detail in Section 4.5.

The social status of a household is determined by randomly drawing a number from a normal distribution with a mean of 5 and standard deviation of 2. The resulting number can be viewed as a score on a hypothetical scale representing an aggregate measure of a household's wealth, occupational prestige and educational attainment. Socio-economic status is measured in many different ways, one being to construct an index from 1 to 10, 1 representing the lower end of the spectrum, and 10 representing the highest. The populations' index scores are then transformed to approximate a normal distribution with a mean of 5 and standard deviation of 2[7]. Previous research used a uniform distribution of social standing, or persuasiveness, but using a normal distribution more realistically portrays the distribution of status in human demography [36]. Household *i*'s social status is represented by S_i in Equation (1). A household's social status remains constant over the course of the simulation.

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[6] Moore neighbourhoods much larger than 32 grid spaces were experimented with in the course of this study but they were found to produce very little change in the end results.

[7] This method of representing socio-economic status is based on that proposed by the Atlantic Centre for Policy Research in Education. University of New Brunswick [36].

A household's media susceptibility is also determined by randomly drawing a number from a normal distribution with a mean of 5 and standard deviation of 2. The number representing media susceptibility can be thought of as a score on a hypothetical questionnaire or similar instrument that measures the level of credibility given to the mass media by the respondent. Once assigned to a household, media susceptibility remains constant over the course of the simulation. Household *i*'s media susceptibility is represented by S_{Mi} in Equation (3).

A number representing the head of the household's reluctance to change their mind, stubbornness, inertia, or resistance to change is simply that agent's social status score multiplied by a constant of two. Previous researchers frequently set the resistance to change parameter, or β in Equation (1), equal to a constant value of two [21, 22, 23]. The reason for choosing two as the resistance to change parameter has no psychological basis, and has not been justified by previous research.

A household's opinion on polio vaccination can be either for (+1) or against (-1). At the beginning of the simulation the analyst sets the proportion of households who support vaccination. Opinions towards polio vaccination are randomly distributed among households regardless of religion, geographic location, or any other attribute. Opinion is the only household attribute that changes over the course of the simulation. It is possible that a household's opinion may change more than once over the course of a simulation.

Although a household in the simulation has seven attributes, it has only one behaviour: to change or maintain its opinion on polio vaccination.

3.4 Simulation Software

The software chosen to build the simulation is the Recursive Porous Agent Simulation Toolkit (RePast). It is based on and borrows many concepts from the well-known Swarm agent-based modelling toolkit[8]. There are several software packages available for these types of agent-based simulation projects, but RePast was chosen for its ease of use, its object-oriented Java implementation, and its large range of examples and templates. RePast also provides support for social network analysis, importation of ArcView shapefiles to incorporate geographic information systems (GIS) information into simulations, and the ability to modify agent properties 'on the fly' at runtime. In a comparison of sixteen agent-based modelling kits, Tobias and Hoffman [30] concluded that RePast was "the most suitable simulation framework for the applied modelling of social interventions".

3.5 Analysis Plan

Although the first and second simulation scenarios described below are quite simple, they describe a baseline upon which to build models of greater complexity and realism. The analysis proceeds as follows:

[8] Swarm Development Group: Swarm 2.2, Available at http://wiki.swarm.org

1. The effect of different initial levels of support for polio vaccination on final levels of support for vaccination is demonstrated on a simulated population of 2,000 households relying on word-of-mouth (WOM) communication as their only means of information diffusion.

2. Using the same population and WOM communication channels as the previous simulation, the effects of different levels of randomness (or volatility) in household decision-making on the success of the simulated polio vaccination campaign are compared.

3. The previous simulation is extended by incorporating mass media communication channels carrying pro-vaccination messages. Different amounts of mass media messages are compared to determine their effect on the population's overall support for polio vaccination.

4. Simulations where only part of the landscape receives vaccination related media messages are carried out in order to examine the extent to which opinions "spill over" via WOM channels from media to no-media areas.

5. Simulations using different population densities are carried out in order to analyse the effect of population density on the process of information transmission and opinion formation.

6. The final simulations incorporate religious sentiment into the agents' psyches by programming them to be less trusting of agents with a different religion to their own. These simulations allow the effects of different levels and distributions of religious tolerance throughout the population on levels of polio vaccination approval to be demonstrated.

4. Summary of Case Study Findings

The objective of this chapter is to present the results of the simulation runs. Much of the analysis relies on visual observation of the direction and magnitude of opinion change and opinion clustering rather than formal hypothesis testing. Support for vaccination (blue households) is randomly spread across the landscape.

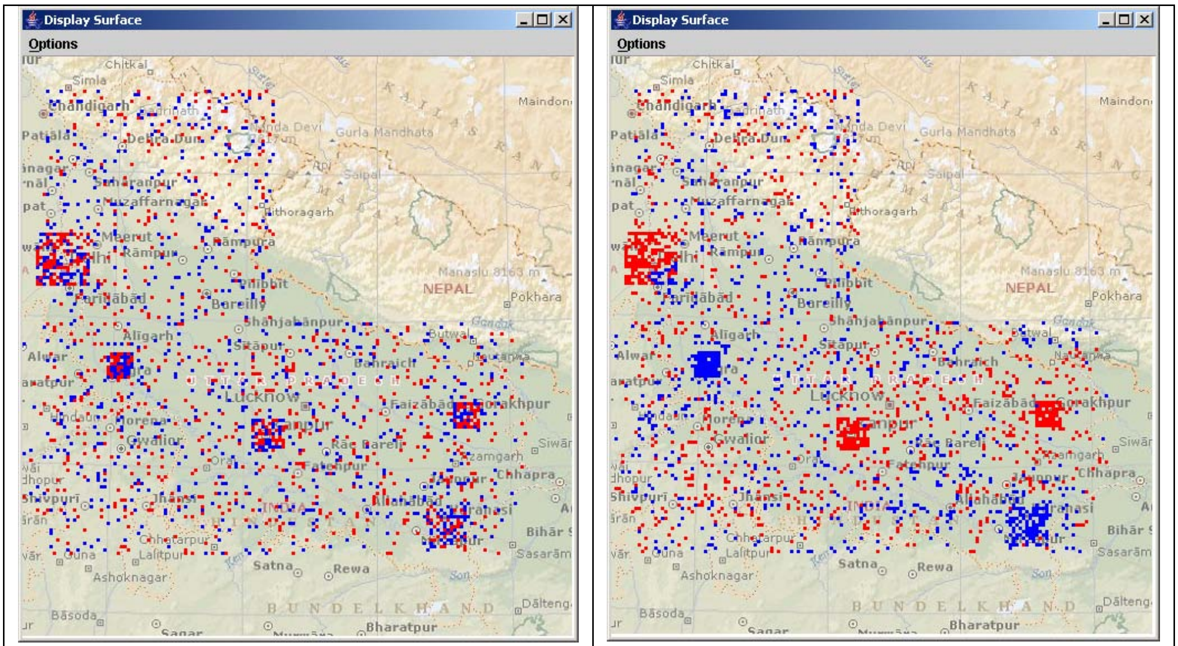
4.1 Influence Through Word of Mouth

The simulation output in Figure 9 presents a situation where there is no mass media attention given to the topic of polio vaccination. Because there is no mass media influence, all information dissemination with respect to polio vaccination is through WOM channels only. This simulation is driven by Equations (1) and (2).

The initial conditions for the simulations presented in this section are:

- Population consists of 2,000 households
- Degree of randomness in individual decision making is held constant for all initial condition levels (T = 20)
- The simulations are run with initial support for polio vaccination in the population set at 20%, 30%, 40%, 50%, 60%, 70%, and 80%.

An example of an initial state with 50% of the population supporting polio vaccination and its resulting final state can be seen in Figure 9.



(a) (b)

Figure 9. Distribution of opinions with 50% initial support for polio vaccination (a) and completed run showing final, or equilibrium, state (b).

The system in its initial state (Figure 9 (a)) has a spatially random distribution of vaccination opinions. By the time a state of equilibrium is reached (Figure 9 (b)) the clustering of like opinions, particularly in areas of high population density, can be clearly seen. The tendency for stable clusters of opinions to emerge from an initially uniform distribution of attitudes is frequently observed in empirical data [18].

The initial level of support for polio vaccination is a major factor in deciding the final (at equilibrium) level of support for polio vaccination. It is imperative to test the sensitivity of simulation outputs to different initial conditions [10]. Figure 10 shows the mean levels of support for vaccination within the target population described in the preceding paragraphs.

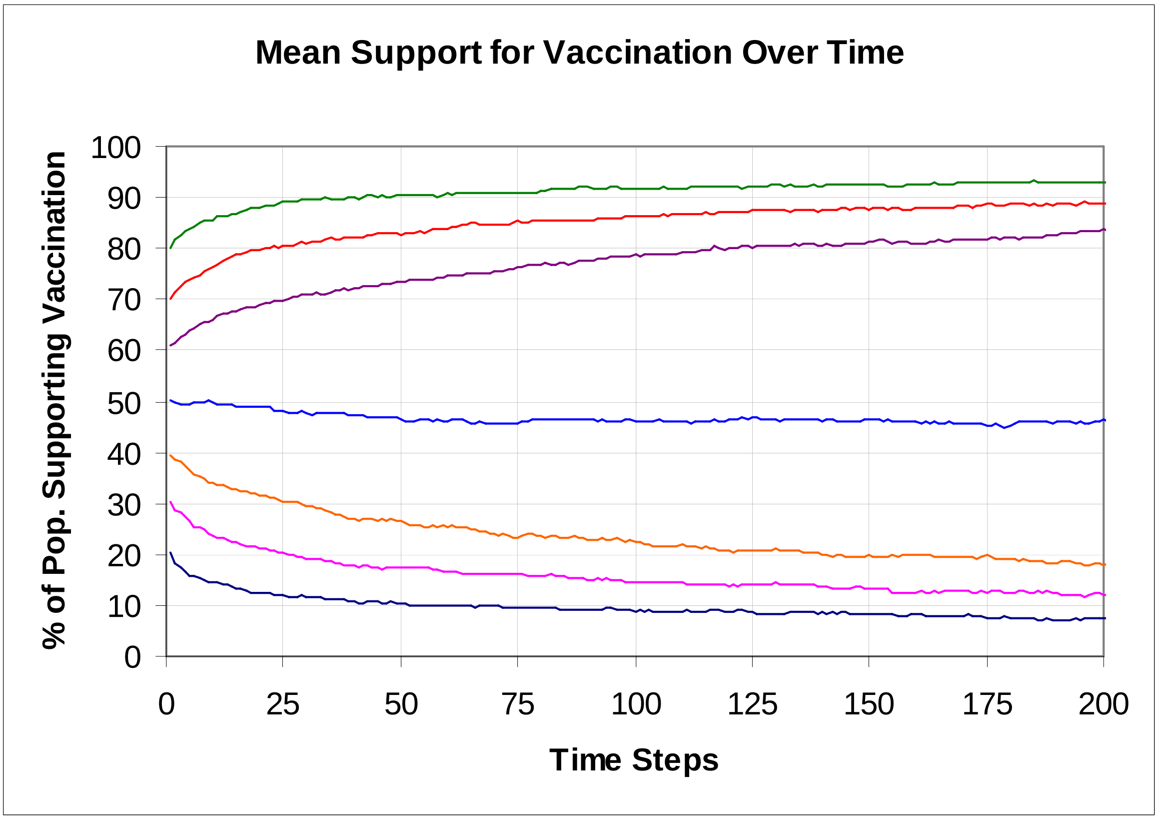


Figure 10. Mean population support for vaccination given different initial conditions.

Twelve simulation runs were carried out at each of seven different initial levels of support (from 20% supporting vaccination to 80% supporting vaccination). Twelve is the minimum number of observations (or runs) required to calculate a confidence interval [32]. The means of n = 12 runs at each initial condition are plotted in Figure 10. The equilibrium or final state appears to be reached after 200 time steps. The time steps denote simulation time, not real-world time. There was no attempt to map or relate simulation time to real-world time.

The initial percentage of the population supporting polio vaccination has a noticeable effect on the final percentage of the population supporting polio vaccination. The effect is not uniform however, as a difference in the initial condition of 10% (from 50% to 40%) results in very different equilibrium outcomes (approximately 50% to 20%, a difference of 30%) than moving from 30% to 20% (still 10%, but equilibrium outcomes are approximately 12% and 8%, a difference of only 4%). These results also agree with Latané's observation that the group or opinion that was dominant in the beginning of his simulations tended to be even more dominant at the end [17].

The simulations demonstrated the typical characteristics of agent-based social simulations, namely similar-opinion clustering, polarization, and the non-linearity of population opinion change over time. The word-of-mouth simulations based on Equation 1 illustrated how the dominant opinion in a population invariably became more dominant. It appears that the greatest increase in the number of people changing their opinions happens when the initial support is closest to the 50% level. Despite their inexorable increase in size, the majority opinion rarely achieved total dominance. Once a simulation had settled into an equilibrium state, there were usually small clusters of agents, often on the boundaries of the landscape, which were able to resist the influence of the majority opinion indefinitely. Agents on or near the boundaries of the grid had fewer neighbours than those closer to the centre due to the truncated nature of their neighbourhoods.

4.2 Volatility in Individual Decision Making

In addition to examining the effects of different initial conditions, parameter sensitivity analysis should also be carried out [10]. One of the most important simulation parameters in this model is T, which represents the amount of arbitrariness, volatility or randomness in individual decision-making (the parameter T was explained in detail in Section 2.3) Figure 11 shows the outcome of using various values of T on population support for polio vaccination. The initial condition of 60% was held constant over all runs and levels of T to minimize variation due to different initial conditions. Twelve runs at eight different levels of T were made and the means plotted on Figure 11. As in the previous section, opinions for and against polio vaccination were randomly distributed over the 2,000 households. The simulations in this section used Equations (1) and (2) to calculate the amount of social influence experienced by each agent.

The initial conditions for the simulations presented in this section are:

- Population consists of 2,000 households
- The degree of randomness in individual decision making (T) is set at 1, 5, 10, 15, 20, 30, 40 and 50
- The initial support for polio vaccination in the population set at 60% for all values of T

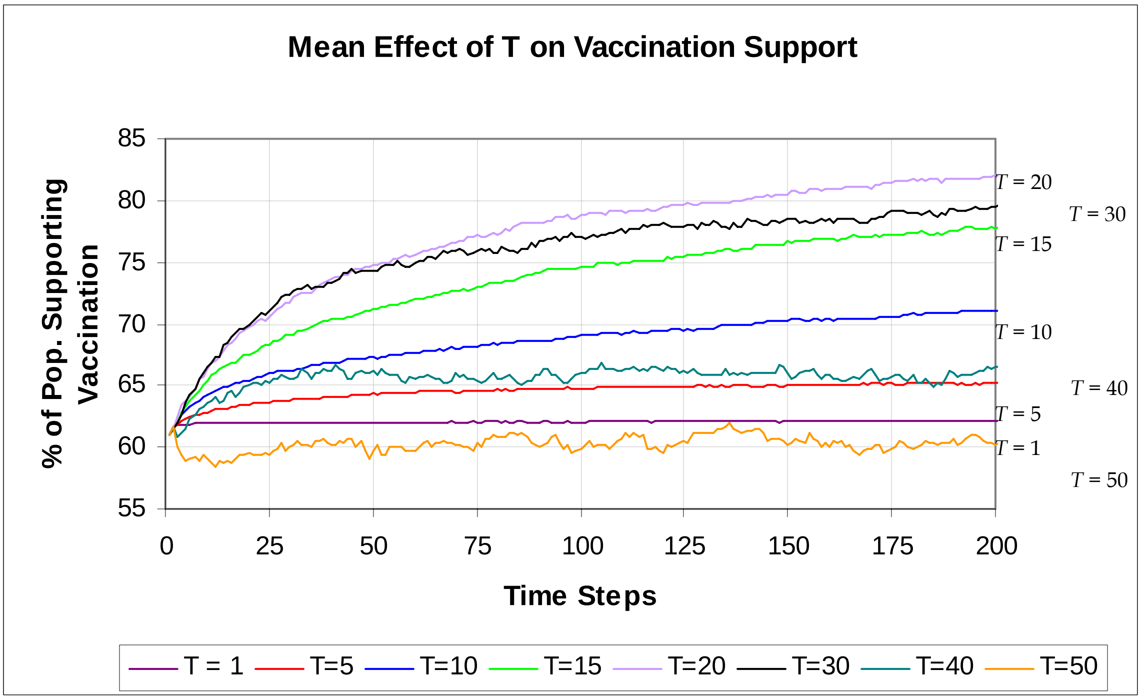


Figure 11. Mean effect of different values of T on support for vaccination.

Varying the value of *T* from 1 to 50 has a noticeable effect on how much the population's support for vaccination grows from the initial condition of 60%. Lower values of *T* (1, 5, and 10) result in smoother and more predictable curves compared to higher values of *T* (30, 40, and 50). As *T* increases, the support for vaccination at the end of the simulation (200th time step) also increases, but only up to values of *T* = 20. Further increases in *T* reverse the trend and result in a lowering of support for vaccination. Figure 12 shows that the strongest effect on support for vaccination is exerted when $T \approx 20$. The reasons for this maximum are not clear. There appears to be an optimal level of volatility in decision-making within the population with respect to increasing an initial majority. The variance in population support for vaccination (60% and 82%) at the 200th time step illustrate the sensitivity of the simulation's results to different values of *T*.

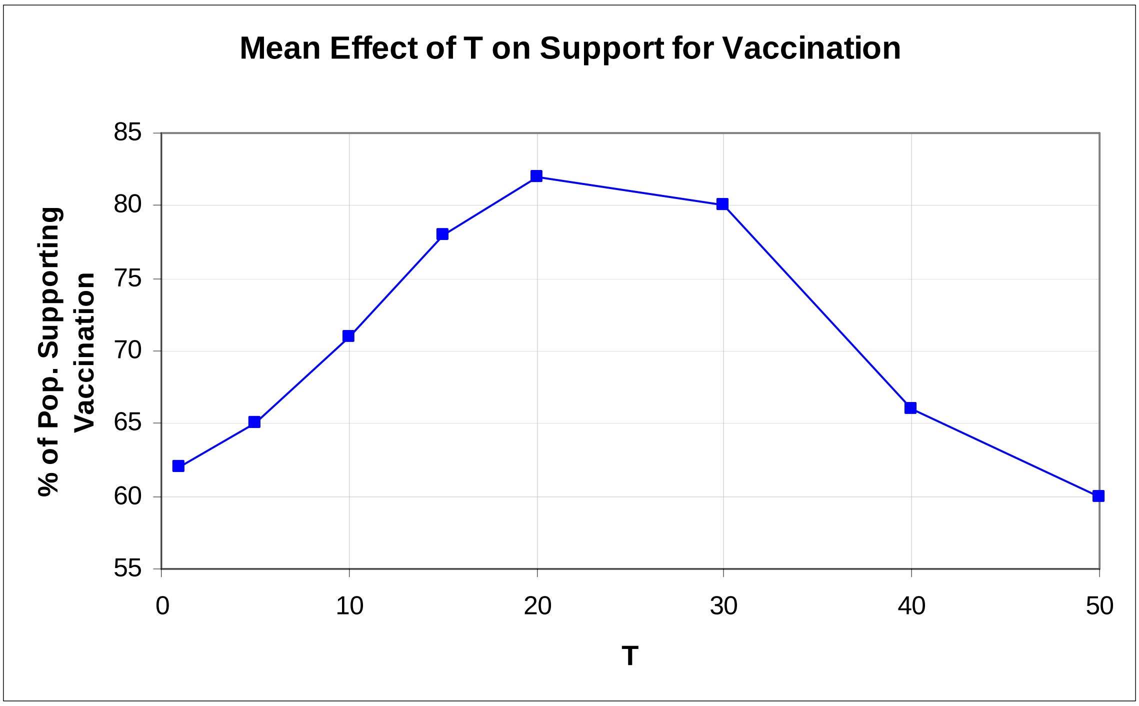


Figure 12. Mean effect of different levels of T on % of population supporting polio vaccination after 200 time steps.

4.3 Simulating Media Influence

Media is considered to be a universal external influence since the combination of the simulation's media opinion parameter, O_M, and each agent's media persuasiveness parameter, S_{Mi}, can act upon every agent in the simulation (see Equation (3)). As in the real world, a media message does not influence all agents equally. Some agents attach a high degree of credibility to media messages, while others attach very little. The amount of credibility an agent attaches to a given media message is normally distributed (see Section 3.3).

The mass media acts like an 'invisible' neighbour to each agent within the simulation and the simulation assumes that each agent has access to this media. By increasing the mean of the random variable representing media susceptibility in the population, S_M, the media's opinion becomes more influential in the decision-making processes of the agents. The simulations in this section use Equation (3) to calculate the amount of social influence experienced by each agent.

The initial conditions for these simulations are:

- Population consists of 2,000 households
- The degree of randomness in individual decision making is constant for all levels of media influence (T = 20)

- The initial support for polio vaccination in the population is set at 50%
- Each agent's media susceptibility, S_{Mi}, is drawn from normal distributions with means of 5, 10, 15 (all with a standard deviation of 2). The condition of *no media influence* is also included for comparison.

Figure 13 shows the effect of increasing media influence (this can also serve as a proxy for the repetition frequency of media messages). In this set of simulations the media's opinion was pro-vaccination (O_M = +1). The initial support for polio vaccination is 50%.

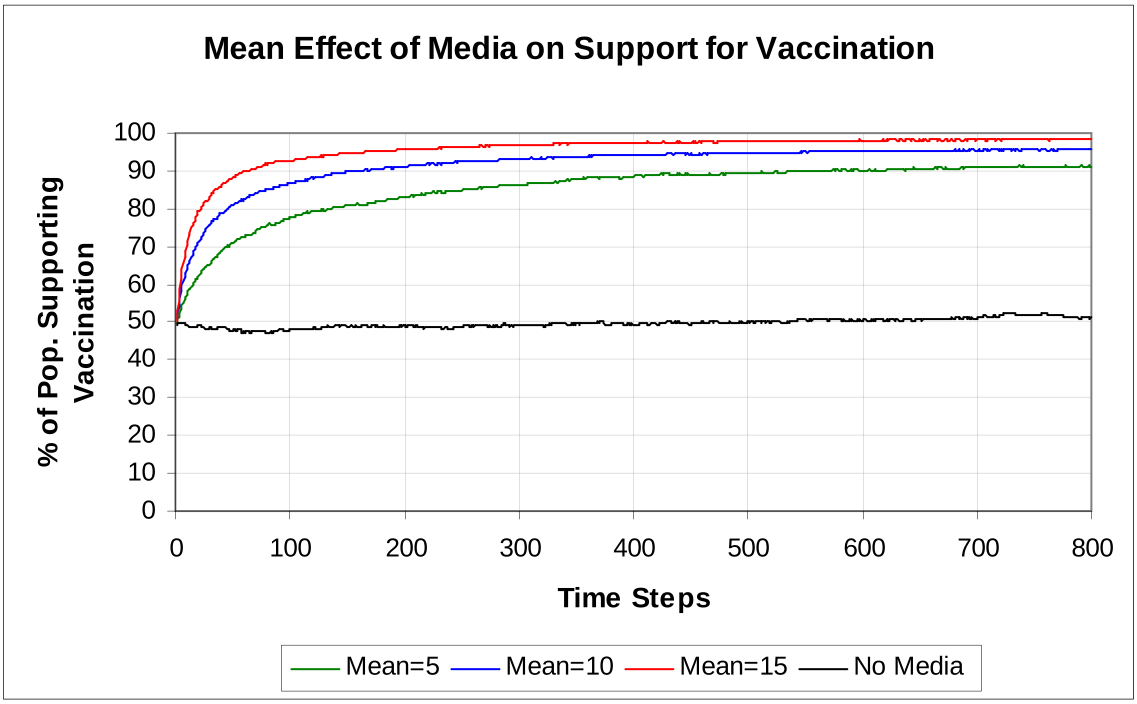


Figure 13. Influence of media on population support for vaccination at 50%.

The non-linear nature of the growth of support for vaccination from an initial starting point of 50% initial vaccination support can be seen clearly in Figure 13. The first few time steps witness the greatest rates of change in population opinion towards polio vaccination, with greater levels of media susceptibility having correspondingly greater rates of change. Even at very high levels of media susceptibility, support for polio vaccination does not always become universal, as there are typically clusters of agents that will not be swayed by the social influence around them. Latané found that minority opinions often survived in a social margin [17]. Nevertheless, compared to the situation where there is no media effect in the simulation, the effect of mass media on population support for polio vaccination is clear.

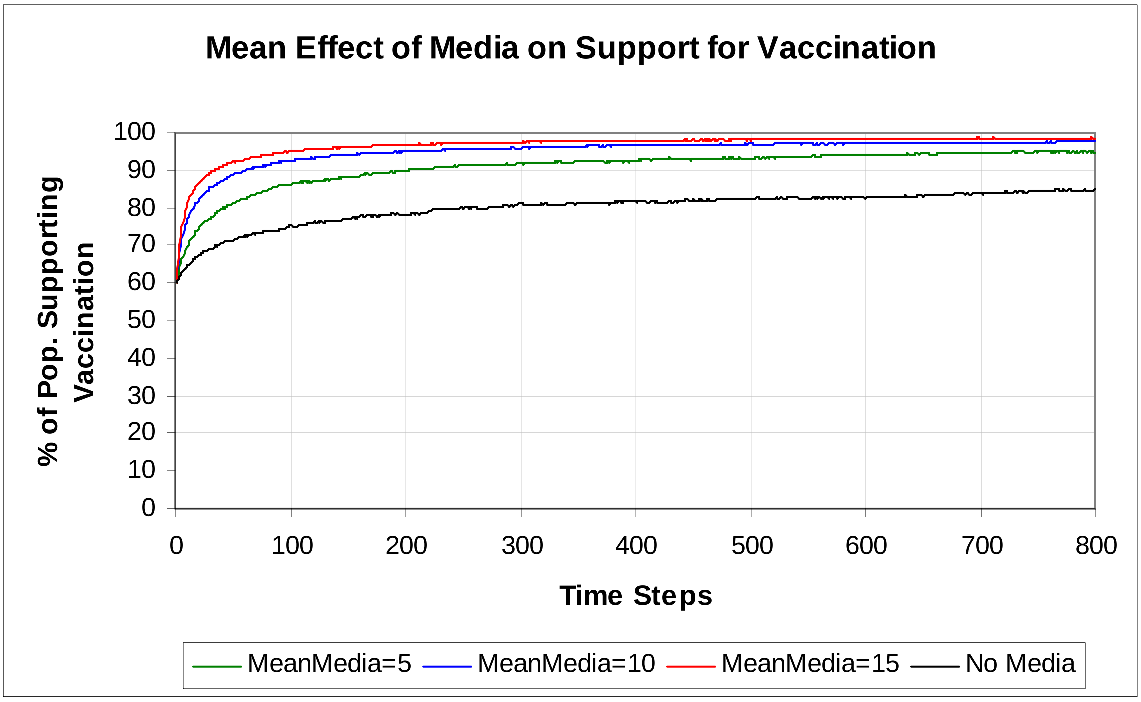


Figure 14. Mean media influence with initial support for vaccination at 60%.

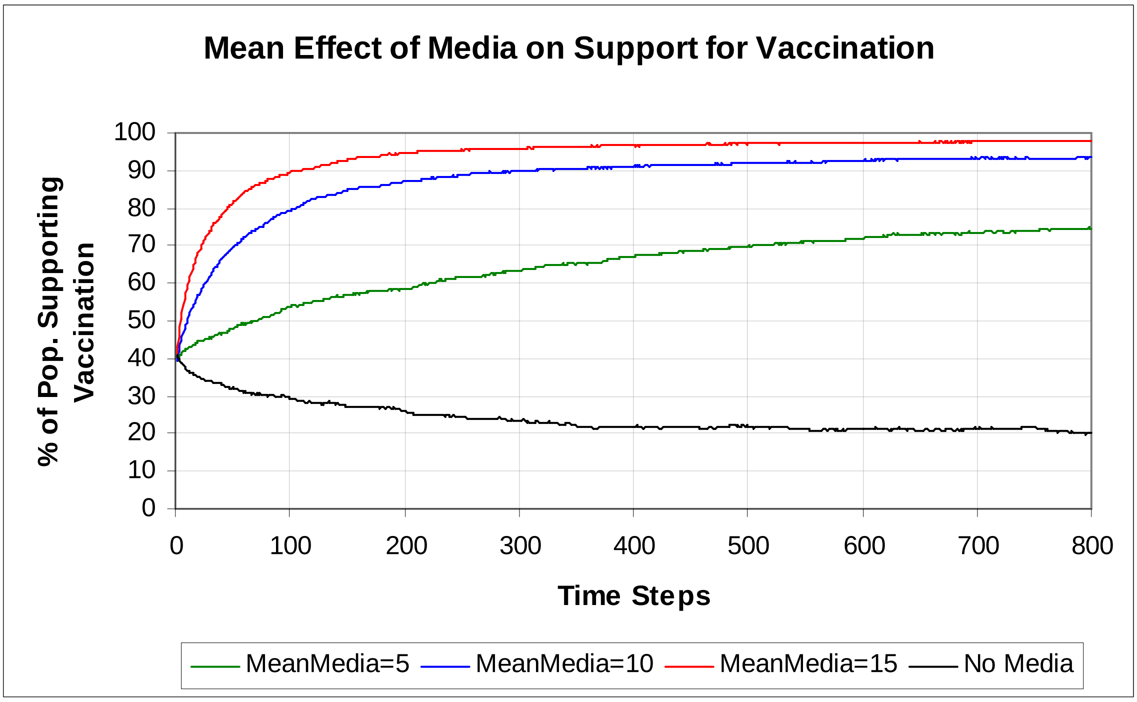


Figure 15. Mean media influence with initial support for vaccination at 40%.

A comparison of Figures 14 and 15 highlights the ability of the media messages to influence the population to support polio vaccination. Even when support for vaccination begins in the minority of only 40% support (as in Figure 15), the two highest levels of media influence quickly shift public opinion above 90%. When mean media influence = 5 the support for vaccination grows much more slowly. The large difference in population support for vaccination at time step 800 in Figure 15 shows the importance of media influence within a population where initial support for vaccination is in the minority. By contrast, the improvement in support for vaccination caused by pro vaccination media messages in Figure 14 is quite small. *Mass media messages appear to give the best return on investment, in terms of increased vaccination support, when the initial support is in the minority.* This is an important result in terms of the cost-benefit analysis that can be carried out using simulation. Once population support is above a certain threshold, human and material resources that would otherwise have provided only small and rapidly diminishing returns could be diverted to areas of greater need.

Future work could enhance the simulation's realism by including multiple media sources, each with different opinions and levels of credibility among different sections of the population. The influence of media such as the Internet, while not as universal as posters, radio or television, could also be modelled.

4.3.1 Geographically Restricted Media Influence

The ability to influence agents using a uniform or varied external influence (which may be regarded as mass-media broadcasts) can be used to conduct experiments on the effects of limiting media influence to only part of the landscape. The simulations in this section use Equation (3) to calculate the amount of social influence experienced by each agent. The population was doubled from 2,000 to 4,000 in this simulation to make it easier to visually demonstrate and assess the effect of restricting media coverage.

The initial conditions for these two simulations are:

- Population consists of 4,000 households
- The degree of randomness in individual decision making is held constant (T = 20)
- The initial support for polio vaccination in the population set at 50%
- The mass media broadcasts have a pro vaccination stance
- Each agent in the broadcast areas has a media susceptibility S_{Mi}, generated by randomly drawing from a normal distribution with a mean = 5 and standard deviation = 2.

Figure 16 (*a*) and (*b*) show two examples of the equilibrium results that typify the effect of deliberately limiting pro vaccination media message penetration to only part of the landscape. The screen shots in Figure 16 are the results of two separate simulations, not before and after screen shots of the same simulation. All vaccination media messages were blocked on the right side of the black dashed line, resulting in noticeably less pro vaccination opinions in these areas. Although the boundary separating broadcast areas from non-broadcast areas (the black dashed line) is crisply defined on the maps displayed in Figure 16 (*a*) and (*b*) and within the simulation itself, there is a degree of permeability in the actual distribution of opinions near the edges of the two areas due to word of mouth information diffusion.

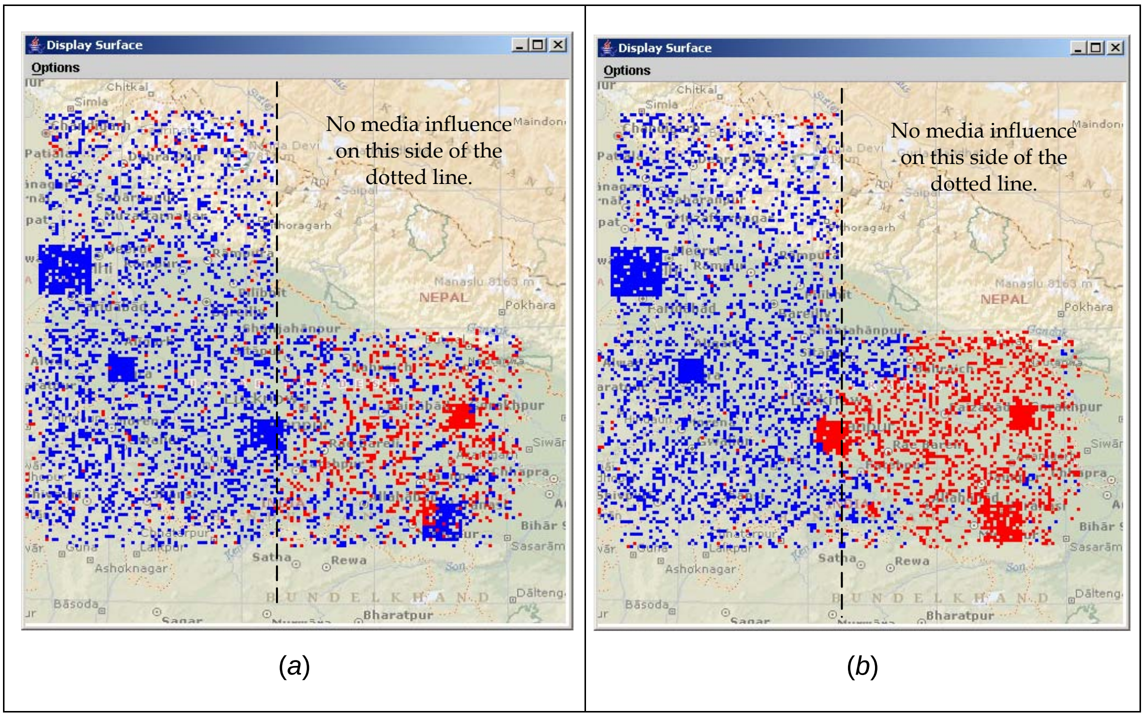


Figure 16. Effect of geographically limited media coverage on final support for vaccination.

Agent-based simulations can provide a vivid illustration of how exposure to media messages can influence a population's opinion on a given topic, as well as how public opinion can be estimated and simulated based on the physical ranges of radio or television. Broadcast black spots due to geographic features or political obstacles can be modelled to give information campaign planners a better appreciation of the boundary penetration of information campaigns into restricted areas. In both simulations shown in Figure 16 the areas that weren't broadcasted to weren't strongly influenced by their neighbours to adopt a pro vaccination stance. Figure 16 (*b*) shows some spill over of opinion, both pro and anti vaccination, along the line bordering the two areas, but the extent of this WOM spill over effect is not great. If the agents were not fixed in position, but free to move about the landscape, the spill over of opinion between media and no media areas may have been greater.

4.4 Social Influence and Population Density

Varying the number of agents on the landscape can simulate the effect of population density on opinion formation and information transmission. Similar opinion clustering is more salient in the densely populated areas of the landscape than the sparsely populated areas. High-density populations mean smaller average distances between target and source and, as a result, greater social pressure is exerted on every individual agent. To explore the effect of population density on support for polio vaccination, a series of simulations using five different levels of population density were carried out. All other factors in the simulation were held constant while the population density of the agents' landscape was varied from high density to low density. The simulation results in this section are produced using Equations (1) and (2).

The initial conditions for these simulations are:

- Population ranges from 7000 households (very high density) to 1000 households (very low density). The five agent population levels are 1000, 2500, 4000, 5500, and 7000
- The degree of randomness in individual decision making is constant for all levels of population density (T = 20)
- The initial support for polio vaccination in the population is set at 60% for all levels of population density
- These simulations do not contain any mass media effects.

Figure 17 shows the mean percentage of the population favouring vaccination from an initial condition of 60% in favour of polio vaccination over different levels of population density. The descriptions of population density, very high to very low, are further defined in Table 5 in terms of total population and the percentage of the grid cells that make up the landscape that are occupied by the agents.

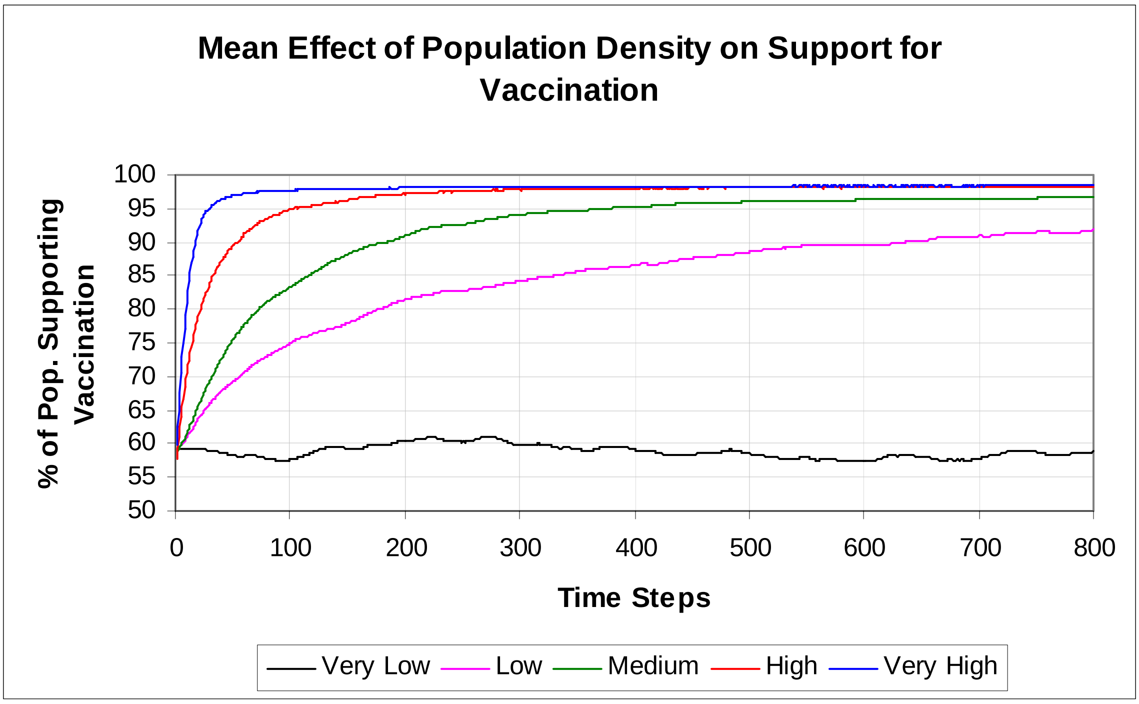


Figure 17. Mean effect of five different levels of population density on population support for polio vaccination.

Table 5. Population density descriptions and their corresponding grid occupation level equivalents.

Population Density	Population	Percentage of Cells Occupied by Agents
Very High	7000	50%
High	5500	38%
Medium	4000	28%
Low	2500	17%
Very Low	1000	7%

Compared to the lower density levels, higher density populations resulted in a larger increase in the percent of the population supporting polio vaccination. The *very low* density simulation (population = 1000) did not show much opinion changing behaviour among agents. This lack of opinion change is understandable when the distance decay of social influence is taken into account. Population density also affected the number of time steps taken to reach simulation equilibrium. Higher density populations reached an equilibrium condition much sooner than the lower density populations.

For an agent to change its stance on polio vaccination, it must be subjected to enough social pressure from agents who hold the opposite opinion on polio vaccination. The much higher levels of social pressure exerted upon agents located within high density landscapes can be seen in Figure 18.

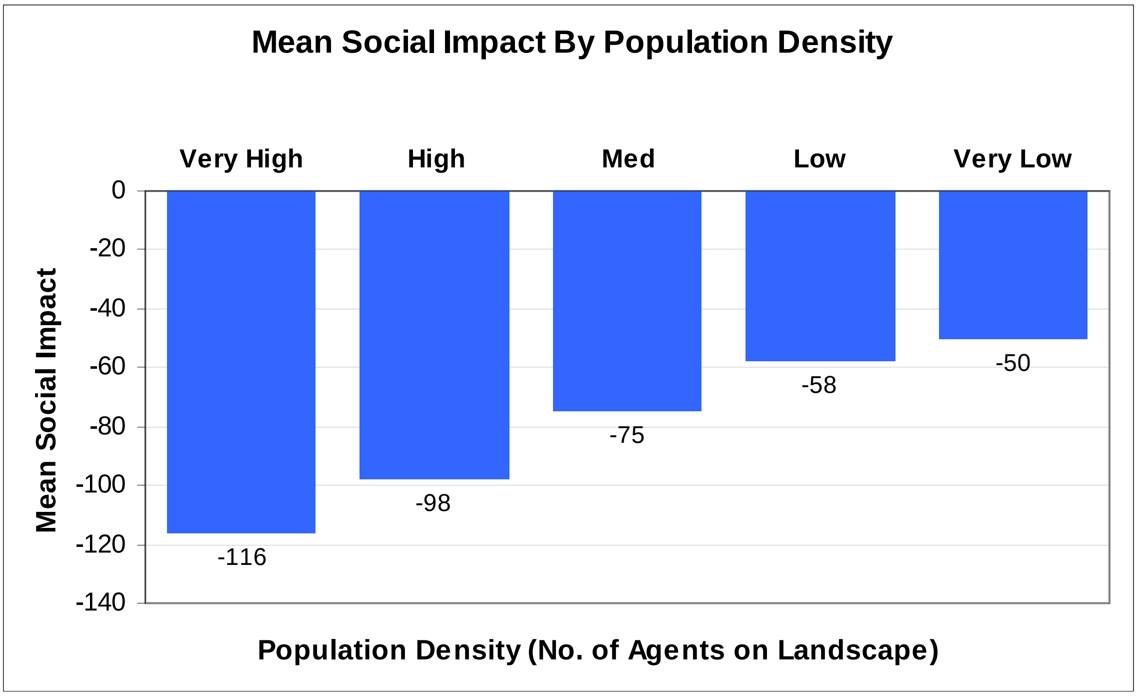
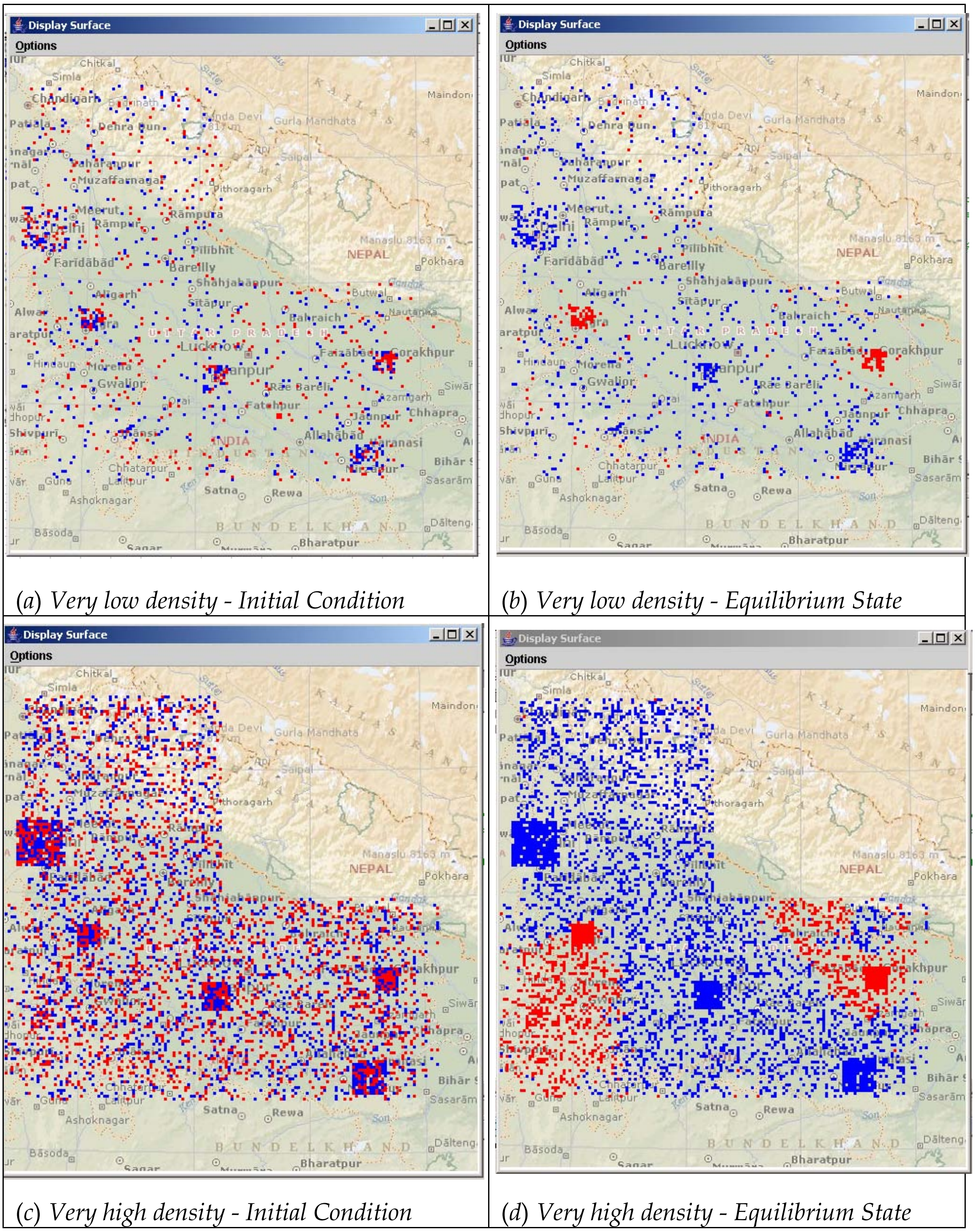


Figure 18. Mean social pressure on target agents at different population densities.

The high level of social pressure experienced by agents whose neighbours are very close drops off rapidly with small changes in the average distance to the nearest neighbour. It is this high level of social pressure when neighbours are very close that leads to clustering of similar opinions. The tendency of like opinions to cluster can be seen in Figure 19, especially in the cities. Figure 19 shows two simulations of low and high population density, both at their initial conditions and at equilibrium.



(a) *Very low density - Initial Condition*

(b) *Very low density - Equilibrium State*

(c) *Very high density - Initial Condition*

(d) *Very high density - Equilibrium State*

Figure 19. Clustering of opinions in low density and high density landscapes.

The more sparsely populated landscape, Figure 19 *a* and *b*, makes it more difficult to visually identify clusters outside of built up areas. Built up areas have a tendency to become all red or all blue, while more sparsely populated areas are less uniform in their opinions. Extremely dense populations such as that in Figure 19 *c* and *d* make it very easy to spot clusters of similar opinions by a simple visual inspection. When the population is more sparsely distributed clusters are harder to identify. The use of quantitative metrics that report the quantity and size of opinion clusters would provide a more accurate way of detecting, measuring, and comparing opinion clusters than simple visual inspection.

Further work needs to be done in assessing the differences in social influence in rural areas compared to cities with respect to the distances or frequency of interactions with neighbours.

4.5 Incorporating Religious Tolerance

In Section 2.4, the rationale and methodology for the incorporation of religious distance into Latané's [17] social impact equation was discussed. This section shows the results of incorporating religious distance into the simulation using Equation (4).

$$I_i = -S_i\beta - O_i O_M S_{M_i} - \sum_{j=1, j\neq i}^{N} \frac{S_j O_j O_i}{\left(w_1 d_{GEO(i,j)} + w_2 d_{REL(i,j)}\right)^2} \tag{4}$$

where

I_i represents the amount of social influence exerted upon individual i.
O_i represents individual i's opinion (±1),
S_i represents individual i's social influence or status ($S > 0$)
β represents an individual's resistance to change ($\beta = 2$)
S_{Mi} represents the strength or influence media messages have on individual i
O_M is the opinion of the media (±1)
O_i is the opinion of individual i (±1)
N is the total number of agents.
$w_1 + w_2 = 1$
geographical distance = d_{GEO}
religious distance = d_{REL}
$1 \leq d_{GEO} \leq 32$
$1 \leq d_{REL} \leq 32$

The distances d_{GEO} and d_{REL} range from 1 to 32 because 1 is the closest distance another agent can be to another agent in the grid and 32 is the maximum distance two agents can receive communications from each other. This was explained in detail in Section 2.7.

In the following simulations, religious distance, d_{REL}, was assumed to first follow a uniform distribution (Sub-section 4.5.1) and then a normal distribution (Sub-section 4.5.2). The differences in shape between the uniform and normal distributions mean that when an agent's religious tolerance is being assigned i.e. randomly drawn from a distribution, comparatively fewer individuals will have a religious tolerance that is at either end of the Bogardus social distance scale [4] when the underlying distribution is normal rather than uniform.

Table 6 shows a side-by-side comparison of the two distributions' frequencies of expressions of the agents' feelings towards other religions. The total number of agents in the population is 2,000. When religious tolerance is normally distributed, the most common feeling expressed towards agents of a different religion is item 3, *would have living in my town or city*. Agents holding very tolerant or very hostile feelings (items 1 and 5 in Table 6) are less numerous under a normal distribution than a uniform distribution.

Table 6. Approximate frequencies of agents' religious feelings towards agents of other religions.

Agent's Feelings Towards Other Religion:	Number of agents expressing this feeling (Normal dist.)	Number of agents expressing this feeling (Uniform dist.)
1. Would have as spouse, friend, or neighbour (1)	150	400
2. Would have in my street or neighbourhood (2-4)	450	400
3. Would have living in my town or city (5-9)	800	400
4. Prefer they live outside my town or city (10-18)	450	400
5. Prefer they live outside my country (19-32)	150	400

The numbers in parenthesis after the statements in Table 6 represent the range of grid spaces that the agent expressing that row's sentiment prefers agents with another religion to be distant. The first column shows how many agents are assigned to the various categories of religious tolerance using a normal distribution, while the second column shows a uniform number of agents in each category of religious tolerance.

Regions where there was genocide or protracted religious and ethnic conflict would be expected to have many of the inhabitants expressing sentiments closer to items four and five if their feelings were measured using the items in Table 6. Being able to quantify the level of hostility or goodwill among different groups is imperative when simulating social processes within heterogeneous populations.

4.5.1 Uniformly Distributed Religious Tolerance

Since both geographic distance and religious distance (transformed into preferred geographic distance) play a part in calculating the social impact one agent will have upon another, the question of how much weight to give to each type of distance arises. Some societies and cultures place a lot of emphasis on religious affiliation, while others place very little [24]. Using Equation (4) to simulate the social influence process makes it possible to compare any differences in population support for polio vaccination that might arise as a result of changing

the amount of weight an agent places on a neighbour's religion. This approach might also inform a separate longer-term information campaign regarding religious intolerance.
The importance of religion was crucial in the polio vaccination case study the simulations were based on, as the incidence of polio among Muslim children was far higher than Hindu children [28]. Rumours were promulgated among Muslim communities that polio vaccination was in fact a Hindu plot to sterilise the Muslims. These rumours led to a distrust of the pro-vaccination messages from the Hindu-dominated Indian Health Department - with tragic consequences for the children involved [28]. In Uttar Pradesh, the proportion of the population that are Hindus is approximately 70%, while Muslims make up approximately 30% of the population. These proportions have been followed when assigning a religion to agents when they are created. Including weighted factors such as religion add to the realism of the agents' attributes and to the social influence processes being simulated.

The initial conditions for the simulations shown in Figure 21 are:

- Population consists of 2,000 households
- 70% of the agents were Hindu and 30% were Moslem
- The degree of randomness in individual decision making is constant (T = 20)
- The initial support for polio vaccination in the population set at 50%
- The weight placed on religion within the simulated society, w_2, was varied over six levels: 0.0, 0.2, 0.4, 0.6, 0.8, and 1.0.

Liberal and democratic countries such as Sweden or the Netherlands or Stalinist regimes like North Korea would be expected to place a very low weight on the religion of a source, while individuals in a theocracy such as Iran or a region with a history of religious conflict, like Northern Ireland, might be expected to place a much higher weight on the religious affiliation of a message's source.

Because of the inclusion of pro-vaccination media messages, the support for vaccination grew from an initial condition of 50% support for all but one of the weights. Medium levels of religious emphasis within society, such as w_2 = 0.6 and w_2 = 0.4, led to the highest levels of polio vaccination acceptance, as seen in Figure 21. The percentage of the population expressing support for polio vaccination is at its lowest when w_2 = 1.0 where there is a total absence of geographic influence in the relationship between source and target.

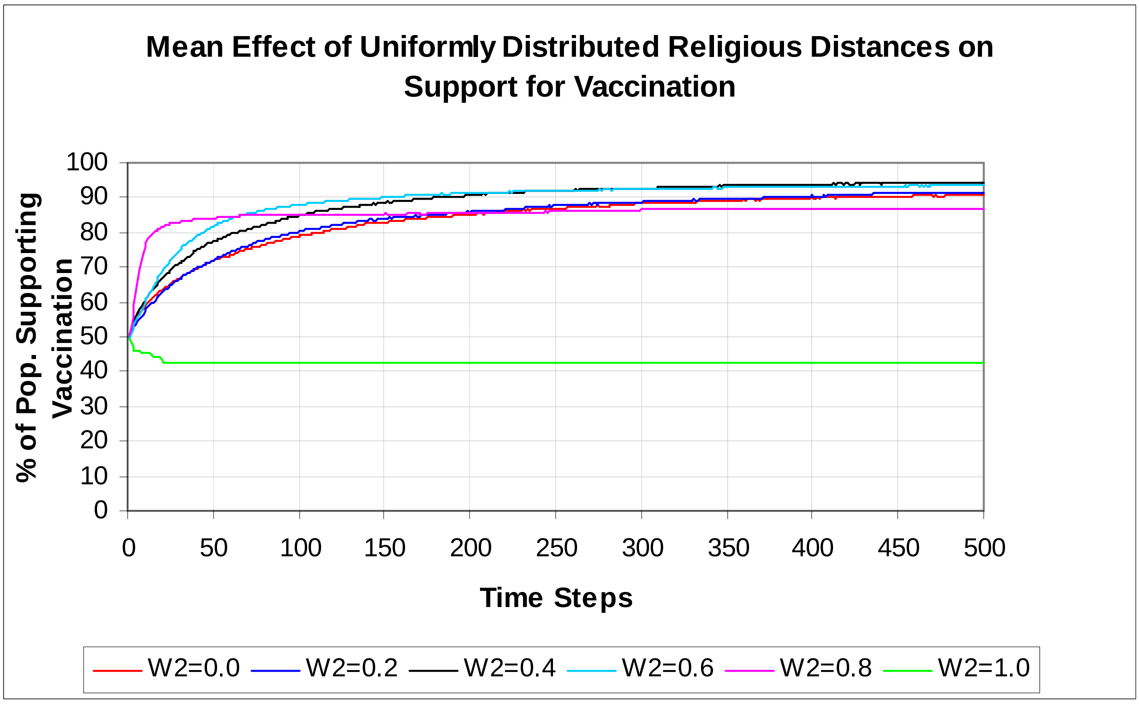


Figure 20. Six levels of weight placed on uniformly distributed religious tolerance.

Apart from the highest religious weight, $w_2 = 1.0$, all other weights produced an equilibrium level of vaccination support above 85%. The rate of opinion change is higher with greater weight on religious affiliation, especially in the first 50 time steps. Why support for vaccination peaks when $w_2 = 0.4$ and then begins to decline as w_2 decreases is not clear. Results that are surprising or have no clear intuitive explanation illustrate the utility of using simulation to provide insights into the complexity arising from different combinations of geographic and religious distance within the framework of dynamic social impact theory.

4.5.2 Normally Distributed Religious Tolerance

If religious tolerance is normally distributed within the population, rather than uniformly distributed, as was the case in the simulations shown in Figure 21, then simulations can be carried out with religious distances reflecting this assumption. Figure 22 shows the same weight levels and initial conditions that generated the previous results displayed in Figure 21.

The only difference between the two sets of simulations is that for the results shown in Figure 22, each agent's religious tolerance was generated using a normal distribution with a mean of 3 and standard deviation of 1 rather than the uniform distribution $U[1, 5]$ used previously[9].

When generating religious tolerance distances from a $N(3, 1)$ distribution, distances less than one or greater than five were discarded and redrawn to ensure that all distances lay between one and five (inclusive). Using integers and truncating the distances at one and five meant

[9] 3 and 1 are used to approximate the mean and standard deviation, respectively, of the uniform distribution $U[1, 5]$ that was used to produce the simulation results shown in Figure 20.

that the distances could not be considered as strictly normal, but they nevertheless provided an adequate approximation for the purposes of this study.

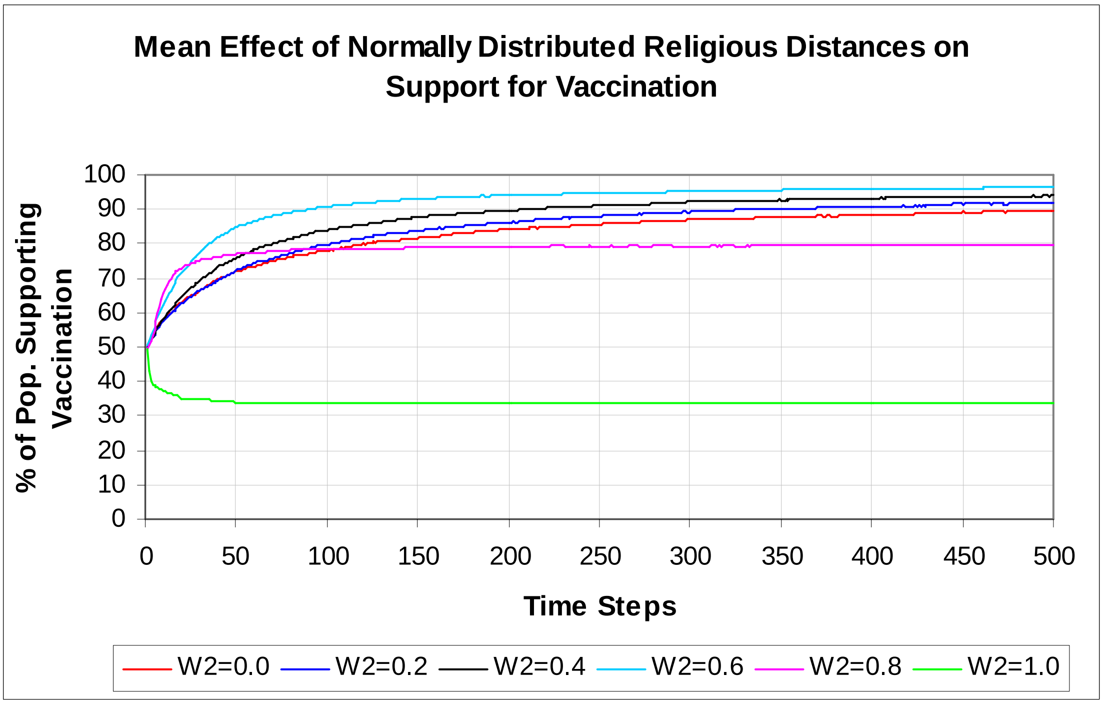


Figure 21. Six levels of weight placed on normally distributed religious tolerance.

The basic pattern of results in Figure 21 resembles that of Figure 20. The highest rate of approval for vaccination was found when $w_2 = 0.6$. Once w_2 was greater than 0.6 there was a gradual lessening of support for vaccination.

As was the case with the uniformly distributed religious tolerance values, the greater the weight religion carried (w_2), the less successful the polio campaign was, but only for larger values of w_2 such as 0.8 and 1.0. Both the normal and uniform distributions resulted in roughly similar outcomes for the same weighting schemes. Both distributions had the effect of a large reduction in support for vaccination when religion was weighted very heavily. Why heavy weights on religion, such as $w_2 = 0.8$ and $w_2 = 1.0$, lead to lower levels of support for vaccination is not clear. Much depends on the shape of the religious tolerance distributions. Different distributions of *preferred* geographic distances interacting with different weighting schemes have the potential to generate an enormous variety of behaviours and outcomes.

The simulation results presented in this section arose from relatively simple interactions among variables and processes intended to represent an individual's religion, religious tolerance, geographic location, social status, neighbours, individual arbitrariness, and the level of credibility they assign to the media. The difficulty in determining why heavy weights on religion, such as $w_2 = 1.0$, lead to lower levels of support for vaccination demonstrates the challenge of modelling the joint effects of several qualitative and quantitative agent attributes and behaviours.

5. Discussion

The objective of this chapter is to discuss some of the assumptions, parameters, and lessons learned in the process of social influence simulation.

5.1 Assumptions and Limitations

The only changeable attribute of an agent is its opinion on polio vaccination. All of the other attributes are given to an agent at creation and remain constant throughout the simulation run. Future research may be able to enhance the simulation's realism by incorporating some run-time agent attribute changes such as changes in an agent's religious tolerance or decreases in an agent's media susceptibility. In reality, opinions on vaccination would already be clustered geographically rather than randomly distributed as was the case in the simulations.

If the agents were not fixed in position, but free to move about the landscape, the spill over of opinion between media and no media areas described in Section 4.3.1 may have been greater.

The time steps denote simulation time, not real-world time. There was no attempt to map or relate simulation time to real-world time.

The number of runs for each combination of factors was $n = 12$. Although greater numbers of runs results in a higher level of accuracy this must be balanced against the time it takes to complete one simulation run. After some experimentation, it was found that 12 runs provided an acceptable compromise between speed and accuracy. It is also the minimum number of observations needed to construct a confidence interval [32]

5.2 Validity and Reliability

Unfortunately, validation and verification of the results of social simulations is not easy. Any simulation involving a large number of parameters makes it hard to comprehensively explore the parameter space. Running a controlled experiment to verify the simulation results of a rare or large event is extremely challenging. Due to the difficulty of validating social simulation results and the generally poor quality of data in the social sciences, very little validation of simulation-based data seems to have been reported in the literature [25]. Validation is especially challenging when many of the modelled properties of the target system are qualitative and the theories that underlie the model are usually described verbally, rather than numerically or symbolically.

5.3 Data Availability

Developing appropriate tools to model and analyse social processes is technically challenging, with numerous hurdles to overcome. The simulation of social processes involves the estimation of many parameters, but sufficient data for making these estimates can be hard to acquire and maintain. Obtaining the requisite data to enable the models to accurately represent a given society represents the biggest hurdle in social simulation today [19]. Nevertheless, simulation always has a valuable role in helping to clarify ideas and theories even if complete validation cannot be carried out [11].

6. Conclusion

This chapter suggests some ideas to improve future studies and summarizes the study's findings.

6.1 Future Work

The two most labour intensive parts of a social simulation project are obtaining a representative sample of the target population to form the basic data set and the development of a valid set of behavioural rules and probabilities to govern the behaviour of the agents. If the data sets and rules of behaviour are well-developed, then simulations that replicate the various issues surrounding social influence will be more reliable, realistic, and credible. Sufficient effort should be expended at the data gathering and behavioural rule generation stages to ensure the accuracy and relevance of the simulation's output.

Social behaviour is easier to predict and represent in simulations if there is a rigid social or organisational structure and a set of cultural mores that are strongly adhered to. Future simulation studies would benefit from focusing on societies where the rules of behaviour are very rigid, such as a military or religious group. Organisations with higher levels of behavioural conformity would be easier to model than organisations where there is much greater diversity and uncertainty in individual behaviour.

More detailed data sets concerning the demographic attributes, behavioural practices of a group, and social networks will be a definite advantage in future model building. Features such as social and geographic mobility, kinship links, the ability to develop or dissolve friendships, increased or decreased levels of social prestige and influence over time, and more complex rules of interaction all add to the fidelity of the simulation. Having a variety of mass media outlets with differing opinions on the issue of polio vaccination would also provide more realism.

6.2 Summary

Agent-based computer simulations have become the most powerful tool in studying the dynamics of social theories [21, 22, 23]. This paper gave an overview of the potential of agent-based modelling within the context of an information campaign. Agent-based simulation enabled the dynamic and emergent properties of social influence campaigns, such as polarization and clustering, to be reproduced and analysed. Although the phenomenon of social change is very complex, applying and extending theories such as the theory of social impact enabled the most critical factors of social influence to be isolated and varied systematically within a very simple model. Further simulations of the kind described in this paper will hopefully be useful in providing insights into the emergence of patterns of cooperation and communication within civilian and military organisations.

7. Acknowledgement

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Tony Wragg

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19. ABSTRACT

Recent military operations in Afghanistan and Iraq have demonstrated the importance of understanding the social processes and power dynamics of local populations. The goal of this study was to simulate the process of social influence within a population using dynamic social impact theory. The simulations reproduced the characteristics of social influence such as opinion-clustering, opinion polarization, minority opinion decay, and the non-linearity of public opinion change. The study demonstrated the potential benefits and limitations of using multi-agent social simulation through a case study of a large scale public health information campaign. The study highlighted the requirement for accurate data concerning a population's social heirarchy, social networks, behaviour patterns, human geography and their subsequent impact on the success of both word-of-mouth and mass media driven information campaigns.